A TIME SERIES ANALYSIS OF FOOD PRICE AND ITS INPUT PRICES

A Thesis

by

KARI FRANCES ROUTH

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Approved by:

Chair of Committee,	James W. Mjelde
Committee Members,	Henry L. Bryant
	James M. Griffin
Head of Department,	C. Parr Rosson

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ABSTRACT

Rapid increases in consumer food price beginning in 2007 generated interest in identifying the main factors influencing these increases. In subsequent years, food prices have fluctuated, but generally have continued their ascent. The effects of crude oil, gasoline, corn, and ethanol prices, as well as, the relative foreign exchange rate of the U.S. dollar and producer price indexes for food manufacturing and fuel products on domestic food prices are examined. Because the data series are non-stationary and cointegrated, a vector error correction model is estimated. Weak exogeneity and exclusion tests in the cointegration space are performed. Directed acyclical graphs are used to specify contemporaneous causal relationships. Dynamic interactions among the series are given by impulse response functions and forecast error variance decompositions.

Weak exogeneity tests indicate all eight series work to bring the system back into equilibrium following a shock to the system. Further, exclusion tests suggest crude oil, gasoline, food CPI, ethanol, and food PPI variables are not in the long-run relationships. Dynamic analyses suggest the following relationships. Ethanol price is not a major factor in domestic food prices, suggesting that food prices are largely unaffected by the recent increased use of corn-based ethanol for fuel. Crude oil prices, corn prices, and the relative foreign exchange rate of the U.S. dollar, however, do influence domestic food prices with corn price contributing the most to food price variability. Innovation

accounting inferences are robust to potential different contemporaneous causal specifications.

DEDICATION

I dedicate this thesis to Dad, Mom, Kelli, Matt, Sara, and Chase. Thank you for your encouragement and support.

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NOMENCLATURE

ADF	Augmented Dickey-Fuller
CPI	Consumer Price Index
DAG	Directed Acyclic Graph
FCI	Fast Causal Inference
GES	Greedy Equivalence Search
PPI	Producer Price Index
RFS	Renewable Fuel Standard
USD	United States Dollar
VAR	Vector Autoregression
VECM	Vector Error Correction Model
VEETC	Volumetric Ethanol Excise Tax Credit

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CHAPTER I

INTRODUCTION

Global food prices have recently become an increasingly important international concern with the occurrence of the food price crisis of 2007-2008. The Food and Agriculture Organization (FAO) food price index, which measures the international prices of meat, dairy, cereals, oils and fats, and sugar, climbed from 127 in 2006 to 159 in 2007 to 200 in 2008 (United Nations 2012). Although this index fell to 157 in 2009 following the 2008 international financial crisis, it has since risen substantially, hitting a historic high in February 2011 (Kovalyova and Brown 2012; United Nations 2012).

Rising prices have fueled a debate over the factors which shape food prices. One component of this debate, dubbed "food versus fuel," centers over whether the increased use of corn and other food commodities for the production of ethanol and other biofuels has led to the historic rise in food commodity prices. Some researchers have concluded that competition for feed grains, especially corn, among ethanol and food producers has initiated a rise in corn prices (Fortenbery and Park 2008; Harrison 2009) and conversion of land towards production of corn for fuel (Westcott 2007; Fabiosa et al. 2010). Others, however, have concluded that biofuel production has not resulted in a significant increase in food prices (Gilbert 2010; Ajanovic 2011). This study adds to the food versus fuel literature by examining factors which may affect food prices, including ethanol.

The objective of this study is to identify how the prices consumers pay for food are affected by the U.S. dollar exchange rate, producer price indexes for both food manufacturing and fuel products, and U.S. gasoline, crude oil, ethanol, and corn prices. Dynamics among these factors are examined using impulse response functions and forecast error variance decompositions. Several points distinguish this study from previous studies. Most previous food studies have used a food commodity price index, such as the FAO food price index, to represent food prices. The food price index, calculated as a component of the U.S. Consumer Price Index (CPI), is employed in this study. The food CPI measures prices that domestic consumers pay for a basket of food goods, as opposed to the FAO food price index which measures price changes in a basket of food commodities that are processed before being sold to end users. By using the food CPI measure, this study offers conclusions about how crude oil, gasoline, ethanol, and corn prices affect prices U.S. consumers pay for food. The producer price index for food manufacturing is used as a proxy for how input costs to food, other than those included individually, affect food prices. Additionally, many food price studies were conducted in the immediate period following the 2007-2008 surge in food prices. This study adds to the literature by including in the analysis data for the years following 2008 as food commodity prices plunged during the worldwide financial crisis and then rebounded to new highs in 2011. By expanding the data range for analysis, the relationships between food prices and the potential causal factors may be better inferred.

CHAPTER II

LITERATURE REVIEW

Potential Causes of Recent Rising Food Commodity and Consumer Food Prices

Abbott, Hurt, and Tyner (2009) addressed the rising prices of food commodities in an update to their 2008 article. They concluded that the primary factors putting upward pressure on food commodity prices – supply and demand, the exchange rate of the U.S. dollar, and the link between agriculture and energy markets – remain the same both before and after the beginning of the 2008 worldwide financial crisis. They included an annotated bibliography of papers, published after June 2008, which addressed rising food prices.

Cooke and Robles (2009) used time series analysis in a study of factors which affect international corn, wheat, rice, and soybean prices. In particular, their goal was to empirically verify the factors which led to significant price increases for these commodities from 2006 to 2008. They concluded that corn, wheat, and soybean price increases in recent years can be at least partially explained by activity in the futures markets. This conclusion contrasts the views of Headey and Fan (2008), who do not believe that speculation in agricultural futures markets is responsible for the 2008 surge in commodity prices.

Rising crude oil prices may be one explanation for the surge in food prices which occurred around 2008. Headey and Fan (2008) and Gilbert (2010) suggested that crude oil price affects agricultural production costs by impacting energy and fertilizer costs.

Higher crude oil prices also raise the marketing costs of food goods through greater transportation and energy input costs to production (Harrison 2009).

The depreciation of the U.S. Dollar (USD) may also be responsible for the surge in food commodity prices that began in 2007-2008 (Headey and Fan 2008; Abbott, Hurt, and Tyner 2009; Baek and Koo 2010). USD depreciation may bring about higher commodity prices for those commodities denominated in USD and for the U.S. in general, because U.S. food commodity exports increase as the dollar depreciates, assuming no other changes. U.S. commodity prices, therefore, will rise for those commodities for which the U.S. is a large exporter (Headey and Fan 2008). Abbott, Hurt, and Tyner (2009) noted that several commodities reached pre-2009 record highs around July 2008 at approximately the same time that the USD exchange rate was at its weakest.

Biofuel production has also been identified as another potential causal factor in the surge of food commodity prices experienced in the first half of 2008. Gilbert (2010), Ajanovic (2011), and Mueller, Anderson, and Wallington (2011), however, contended that biofuel production was not the main contributor to the 2008 surge in food prices. Mueller, Anderson, and Wallington (2011) supported this view by arguing that the prices of food commodities fell significantly below their 2008 highs in 2009-2010, although biofuel production was still increasing. The evolving relationship between agricultural and energy markets in the context of rising ethanol production is discussed further in the next section of the literature review.

To my knowledge, only one other study has attempted to identify factors which affect consumer food prices as opposed to food commodity prices. Baek and Koo (2010) employed the Bureau of Labor Statistics' U.S. food CPI to represent consumer food prices. Using cointegration analysis and a vector error correction model (VECM), Baek and Koo (2010) determined that agricultural commodity prices, the USD exchange rate, and energy prices affect consumer food prices in the long-run. In the short-run, however, only agricultural commodity prices and the exchange rate are important influences on food prices.

Although Baek and Koo's (2010) original analysis began by examining the effects of U.S. agricultural commodity prices, U.S. energy prices, the exchange rate, and fuel ethanol production on consumer food prices, they excluded the ethanol production variable in cointegration analysis because it was found to be stationary in one of their two subsample periods. The Perron procedure was utilized to determine that, because of the presence of a structural break, the data sample should be split into two data sets: set I January 1989 – October 1998 and set II November 2001 – January 2008. The authors estimated a VECM using subsample II and cointegration results suggesting two cointegrating vectors. They found that both consumer food price and agricultural commodity price adjust over a period of months to bring the system back into equilibrium. Additionally, Baek and Koo (2010) found a two-way short-run relationship between food prices and agricultural commodity prices, because food price is influenced by lagged commodity price changes, which are in turn influenced by lagged food price changes.

Relationship between Agricultural and Energy Markets

Many studies have addressed the recent transformation of the relationship between agricultural and energy markets that has occurred with the growth in ethanol production. Most ethanol in the United States is made from corn; therefore, expansion of the ethanol market has implications for the agricultural sector (Westcott 2007). Researchers that have examined the effect of ethanol production on the corn market have concluded that growth in the ethanol industry is a factor in explaining recent rising corn prices (Westcott 2007; Fortenbery and Park 2008; Harrison 2009). Fortenbery and Park (2008) separated the demand for corn into three separate categories: feed demand, export demand, and food, alcohol, and industrial demand. The food, alcohol, and industrial demand category was found to have the largest impact on corn price. Furthermore, despite the fact that use as feed remains the highest demander of corn, feed use was not found to be statistically significant in determining corn price. This led the authors to conclude that the growing demand for corn from the ethanol industry (a component of the food, alcohol, and industrial demand category) is an important factor in explaining corn price.

Serra et al. (2011) employed a smooth transition vector error correction model to investigate the possibility of asymmetric patterns of price transmission among ethanol, corn, crude oil, and gasoline prices in the United States. Using monthly nominal price data from 1990 to 2008, they found that the ethanol market provides the primary channel through which corn prices connect to energy prices. Serra et al. (2011) found that a rise in ethanol prices, when this market is far from its equilibrium, results in corn price increases, an effect which remains statistically significant for eight months after the price shock. Another outcome observed when the ethanol market is far from its equilibrium is that a shock in corn price produces the same directional change in the ethanol price, a change that peaks in size after approximately three months.

Tyner (2010) noted the growing correlation between crude oil, gasoline, and corn prices that began around 2006, just as the ethanol industry commenced a period of rapid expansion. The nature of the relationship between these commodity prices, however, changed in 2009. Ethanol production facilities ceased the use of two billion gallons of ethanol production capacity out of a total of 12 billion gallons as the price of ethanol plummeted. At about the same time as these changes in ethanol production were taking place, the price of ethanol became strongly connected to the price of corn. The correlation between ethanol and corn rose from 0.04 between 2006 and 2008 to 0.84 in 2008-2009. Tyner (2010) describes the origin of this strong correlation between corn and ethanol prices as follows:

> "The economics is such that in a market that is surplus in ethanol as in summer 2009, the price of ethanol is driven more by the price of corn as the surplus production capacity drives the price of ethanol down to the breakeven price given the corn price" (Tyner 2010, p. 201).

Westcott (2007) described the effects of rising corn prices on both corn acreage and the livestock industry. He predicted a reduction in the total share of corn use by the livestock industry, currently the largest demander of U.S. corn, as a result of higher corn prices (Westcott 2007). Additionally, a higher corn price increased the planted acreage devoted to corn, while reducing that available to other crops (such as wheat and oilseeds) as land shifts toward corn production (Westcott 2007; Fabiosa et al. 2010).

Zhang et al. (2009) explored the relationship between ethanol, gasoline, crude oil, corn, and soybean prices. They found no evidence of long-run relationships between fuel and agricultural commodities. Rather, they concluded that corn price increases in recent years may be caused by an increase in the demand for ethanol (i.e., ethanol demand may be responsible for price increases in the short-run), but that this price will return to its equilibrium level in the long-run. This result contradicts that of other studies (Serra et al. 2010, 2011) whose cointegration results indicate a long-run price relationship between corn and energy commodities.

Several studies examined the evolving relationship between crude oil and corn prices (Banerjee 2011; Hertel and Beckman 2011). Banerjee (2011) noted that corn demand (which is derived from the demand for ethanol) has a positive cross-price elasticity with crude oil prices because ethanol is considered a partial substitute for crude oil. A rise in crude oil price will increase the demand for corn for ethanol production. Before the growth of the ethanol industry, increases in the price of crude oil only led to corn price increases because crude oil is an input to corn production. The findings of Banerjee (2011), however, showed that, subsequent to ethanol industry growth, corn price has been affected by crude oil price not only on the supply side, but on the demand side as well. Hertel and Beckman (2011) stated that the strength of the relationship between corn and crude oil prices varies relative to whether crude oil price is high or low.

Other studies document a relationship between gasoline and ethanol prices. Du and Hayes (2009) concluded that increased ethanol production has a statistically significant negative effect on gasoline prices; therefore, as ethanol production has risen, gasoline prices have declined. Different regions of the country, however, were found to have experienced varying levels of retail gasoline price reductions. Additionally, they found that this decrease in gasoline prices lowered gasoline refiners' profits. Serra et al. (2011) found that a rise in gasoline price follows a rise in ethanol price when the ethanol market is in disequilibrium. They postulated that higher ethanol prices drive up production costs of blended gasoline (whose price is strongly correlated with gasoline price), leading to a decrease in blended gasoline supply and an increase in its price. A rise in gasoline prices, however, resulted in an observed decline in ethanol prices. Gasoline price increases generated blended gasoline price increases because of their aforementioned strong correlation, resulting in decreasing demand for both blended gasoline and ethanol, and consequently, falling ethanol prices. Luchansky and Monks (2009) also found that gasoline price increases elicited a strong negative effect on ethanol demand in their estimation of ethanol market supply and demand elasticities.

The Corn Market, the Ethanol Market, and the Role of Government Policy

Several studies have addressed the effects of government mandates, subsidies, and additional supports on both the corn market and the ethanol market. One support for the ethanol market is the Renewable Fuels Standard (RFS) created by the Energy Policy Act of 2005, a regulation requiring that all gasoline include a minimum amount of renewable fuels (Energy Information Administration [EIA] 2011a).

The Volumetric Ethanol Excise Tax Credit (VEETC), or “blender’s credit,” gave fuel blenders a federal tax credit for each gallon of ethanol blended into their gasoline. Introduced by the American Jobs Creation Act of 2004, the VEETC was originally set at 51 cents per gallon. The tax credit was subsequently reduced to 45 cents per gallon as part of the 2008 Farm Bill. This tax credit expired on December 31, 2011. Additionally, an import tariff of 54 cents per gallon is levied on ethanol from other countries to encourage blenders to use domestically-produced ethanol (Renewable Fuels Association 2012).

Devadoss and Bayham (2010) provided evidence that a decrease in corn subsidies for farmers predictably resulted in a decrease in corn production, followed by an increase in corn price. The rising corn price then caused the production of corn-based ethanol to slow and ethanol price to increase. When Devadoss and Bayham (2010) imposed the binding mandate from 2009 (requiring 10.5 billion gallons of ethanol be blended into the fuel supply) simultaneously with the crop subsidy reduction, the effects of the subsidy reduction were negated by the increased demand for ethanol.

Kim, Schaible, and Daberkow (2010) examined the effects of both tax credits and blending mandates on fuel markets. As a biofuel tax credit increased, the prices of fuels fell. These same fuel prices, however, increased as the rate of the blending mandate rose. As the blending mandate increases, the marginal production costs of gasoline increase, resulting in a leftward shift of its supply curve. Similarly, Kruse et al. (2007) looked at the influence of the ethanol tax credits and import tariffs on industry production. They concluded that the elimination of both the ethanol tax credit and import tariff would lead to a 30% reduction in ethanol production.

Thompson, Meyer, and Westoff (2009) concluded that the ethanol mandates increase the sensitivity of ethanol prices to corn yields and disrupt the relationships between ethanol use and ethanol price. Their market simulation results exhibited a notably lower correlation between ethanol price and use in the scenario in which the mandate was present compared to the scenario in which the mandate was absent.

Anderson and Coble (2010) studied the effects of ethanol blending mandates on the corn market. They noted that ethanol blending mandates impact the derived demand for corn. Anderson and Coble (2010) argued that even a nonbinding ethanol blending mandate can affect equilibrium corn prices and quantities:

> "What is overlooked in this argument [that the removal of RFS mandates will have little effect on corn prices because the mandate is currently nonbinding] is the critical role of expectations in price discovery. Although the RFS may be currently nonbinding, in effect it can still be seen as an indirect support for corn prices. Market participants know that if the supply and demand situation in the corn market changes, the RFS mandate will become binding, providing strong support for prices" (Anderson and Coble 2010, p. 50).

Feng and Babcock (2010) found that government ethanol subsidies and mandates initiate land use changes which may potentially expand total cropland acreage. Higher subsidies and mandates resulted in increases in total cropland. The impact of yield improvements on land use allocation, however, differed between mandates and subsidies. With government subsidies, higher yields led to a rise in planted acreage; higher yields under government mandates may do the opposite, shrinking the amount of land used for agricultural production because the demand can be met with fewer planted acres.

Finally, Elobeid and Tokgoz (2008) examined how the removal of the U.S. ethanol trade tariff would affect the ethanol market. The ethanol tariff has been successful in supporting the U.S. ethanol industry, resulting in a U.S. ethanol market that is practically independent of the world market. Removal of the tariff would reduce both domestic ethanol prices and production. U.S. net imports of ethanol would increase, resulting in an increase in world ethanol price.

CHAPTER III

DATA AND METHODOLOGY

Data

Eight monthly series representing national level data, spanning January 2000 through February 2012, are used in the analysis. These eight series include: crude oil prices, gasoline prices, ethanol prices, corn prices, food price index, producer price indexes for both food manufacturing and fuel products, and U.S. dollar index. Monthly prices are used, because the food price index is only reported on a monthly basis.

Crude oil and gasoline prices are included to examine the roles of these energy commodities in determining food prices. Crude oil prices, represented by the West Texas Intermediate (WTI) spot price in dollars per barrel, and monthly retail gasoline prices in dollars per gallon are from the Energy Information Administration (EIA 2012a, 2012b). Ethanol prices, in dollars per gallon, are represented by the monthly average of weekly prices from over 30 cities across the United States (Hart's Oxy-Fuel News 2012). By including ethanol prices in the analysis, there is an opportunity to add to the literature of the "food versus fuel" debate. Additionally, corn price is included, because it is an input to both ethanol and many processed food items. Corn prices are represented by a national No. 2 Yellow corn price. Daily prices were converted from cents per bushel to dollars per bushel then averaged to obtain the monthly prices (Datastream 2012).

The food price index, which represents consumer food prices in the analysis, is calculated by the Bureau of Labor Statistics (BLS) as a component of the Consumer

Table 3.1. Descriptive Statistics of the Data Series

Series	Mean	Standard Deviation	Minimum	Maximum	Coefficient of Variation
		Non-logged Prices and Indices			
Crude Oil	57.71	27.68	19.39	133.88	.48
Gasoline	2.33	0.78	1.13	4.11	.33
Corn	3.18	1.54	1.49	7.33	.48
Food CPI	196.85	19.75	166.60	232.56	.10
Ethanol	1.89	0.55	0.94	3.64	.29
Food PPI	153.63	20.21	126.70	196.40	.13
Fuel PPI	152.28	43.80	82.50	268.70	.29
Dollar Index	110.93	10.06	94.62	129.69	.09
		Natural Logarithms of Prices and Indices			
Crude Oil	3.94	0.50	2.96	4.90	.13
Gasoline	0.79	0.34	0.12	1.41	.43
Corn	1.06	0.43	0.40	1.99	.41
Food CPI	5.28	0.10	5.12	5.45	.02
Ethanol	0.59	0.29	-0.06	1.29	.49
Food PPI	5.03	0.13	4.84	5.28	.03
Fuel PPI	4.98	0.29	4.41	5.59	.06
Dollar Index	4.70	0.09	4.55	4.87	.02

Price Index (CPI). The base years are 1982-1984 (Bureau of Labor Statistics [BLS] 2012a). Costs of inputs to both food and gasoline, other than the corn and crude oil prices already included, could not be obtained. As such, two proxies for these input costs are used. The producer price index (PPI) for fuels and related products and power, a proxy for the input costs of fuels, is from the BLS, with a base of 100 for 1982 (BLS 2012b). The PPI for food manufacturing, acting as a proxy for other input costs to food prices, is also from the BLS with a base of 100 for 1984 (BLS 2012c). Finally, the U.S.

Dollar Index, from the Federal Reserve Board of Governors, is a trade-weighted average of the U.S. dollar's foreign exchange value for the currencies of our largest trading partners, including those of Europe, Canada, Japan, Mexico, China, the United Kingdom, and Taiwan, among others. The base value of 100 corresponds to January 1997 (Board of Governors of the Federal Reserve System 2012). By including the dollar index, the effect of the U.S. dollar's foreign exchange rate on U.S. food prices can be examined.

All data analysis was performed using the natural logarithms of the prices and price indices. A summary of the descriptive statistics for all eight variables (series) in the dataset is provided in table 3.1. Note that both crude oil and corn prices have the largest variability as measured by the coefficient of variation followed by gasoline price. Additionally, graphs of the logarithmic form of each price series are provided in figure 3.1. With the exception of the U.S. Dollar Index, all series show an increasing trend. Graphs for both crude oil and gasoline reveal that these prices appear to move more closely together than the other series. Methodology is discussed in the remaining paragraphs of this section.

Stationarity

A stationary time series is one that oscillates around its mean and does not include a trend (Lütkepohl 2004a). Economic time series, however, are generally non-stationary. Cointegration analysis is one solution for the problem of non-stationary variables (Juselius 2006). Augmented Dickey-Fuller (ADF) tests are used to initially check for

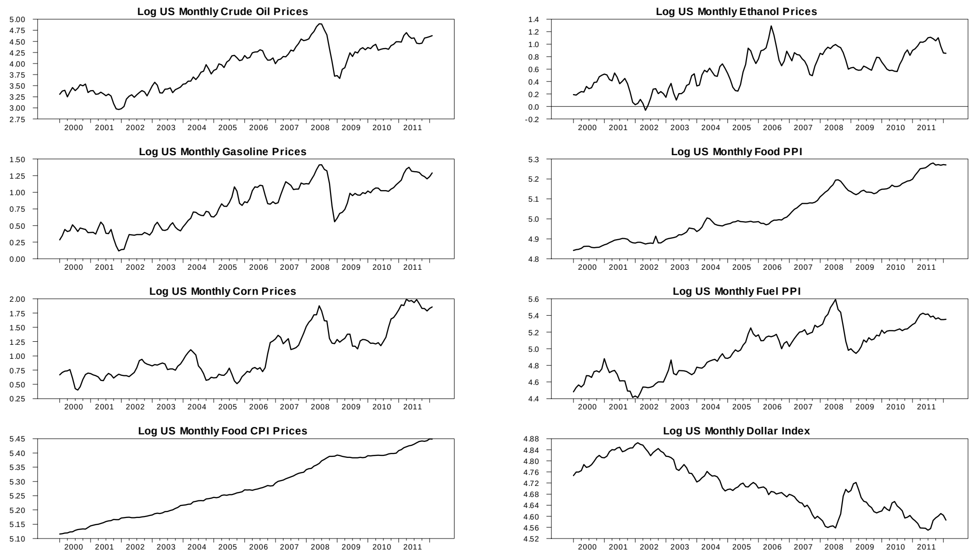

Figure 3.1. Graphs of Each Series in Natural Logarithms for Monthly Data from January 2000 - February 2012

series stationarity. In the ADF tests, a series is deemed stationary if the null hypothesis that a unit root exists is rejected. The following regression is estimated by ordinary least squares (OLS) (Lütkepohl 2004a):

$$\Delta x_t = b + \phi x_{t-1} + \sum_{j=1}^{p-1} w_j \, \Delta x_{t-j} + u_t \tag{1}$$

where Δ is the difference operator, *x* represents the series at time *t*, *b* is a constant, p is the number of lags, ϕ and w_j are coefficients to be estimated, and *u* is an error term. The t-test statistic of ϕ is compared to the appropriate critical values, which can be found in Fuller (1996). The ADF test is performed with zero to 11 lags to test for stationarity. The appropriate lag order can be determined by examining the Schwartz Information or the Hannon and Quinn criteria.

VECM

The data generation process of a specified set of time series variables is often illustrated by a vector autoregressive (VAR) model. According to Lütkepohl (2004b), however, cointegrated variables should be analyzed using a vector error correction model (VECM) rather than the VAR form. Lütkepohl (2004b) describes cointegrated variables as those having "…a common stochastic trend" (p. 87). Additionally, Juselius (2006) gives two advantages of using a VECM over a VAR to model time series data. First, the effect of multicollinearity is smaller. Second, the VECM separates the long-run and short-run effects. These advantages, in addition to the non-stationarity of the data series, lead to the use of the VECM for model estimation. The starting point for describing and estimating a VECM is a VAR, as such, the discussion begins with a description of a VAR. The notation here follows that employed by Lütkepohl (2004b, p.88).

A VAR of order p is:

$$y_t = c + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \tag{2}$$

where y_t is a (K × 1) vector of the variables of interest at time t, K is the number of series in the model (where K equals eight in this study), c is a (K × 1) vector of constant terms, the A_i is a (K × K) matrix of coefficients to be estimated, p is the number of lags, and u_t is a (K × 1) vector of error terms. The error term is assumed to have a zero mean and a covariance matrix equal to $E(u_t u_t') = \Sigma_u$ (Lütkepohl 2004b).

The VECM of the levels VAR model in equation (2) has p – 1 lags and is written as (Lütkepohl 2004b, p. 89):

$$\Delta y_t = c + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \cdots + \Gamma_{p-1} \Delta y_{t-p+1} + e_t \tag{3}$$

where Δ is the difference operator, $\Pi = -(I_K - A_1 - \ldots - A_p)$, $\Gamma_i = -(A_{i+1} + \ldots + A_p)$ for $i = 1, \ldots, p-1$, and e_t is the error term. The Γ_i terms are the short-run parameters, while Π are the long-run parameters. The VECM in equation (3) is derived by subtracting y_{t-1} from both sides of the levels VAR given by equation (2). Additionally, it can be shown that matrix Π can be decomposed into two matrices α and β of dimension $K \times r$. These matrices can be multiplied to obtain the $(K \times K)$ matrix Π, such that $\Pi = \alpha\beta'$. The rank of Π, equal to r, is known as the cointegration rank (Lütkepohl 2004b).

Estimation of a VECM usually begins with the determination of the lag order of the VAR. OLS is employed to separately estimate each of the K equations of the VAR model in equation (2). The OLS estimator has an equivalent efficiency to the generalized least squares (GLS) estimator provided all equations contain the same number of lags and variables (Lütkepohl 2004b). VARs of lag order zero to 11 are estimated. The lag order is determined by examining the Schwartz Information, Akaike Information, and Hannon and Quinn criteria.

The trace test, also called the Johansen test, is used to determine r, the cointegration rank. Juselius (2006, p. 140) describes the cointegration rank as follows, “The cointegration rank divides the data into r relations towards which the process is adjusting and p-r relations [p is the number of variables in the model in Juselius (2006)] which are pushing the process.” The cointegration rank is determined using a series of tests. The trace test statistic for the null of K-r unit roots is compared to the appropriate critical value as found in Appendix A of Juselius (2006). Beginning with $r = 0$, the null of K-r unit roots is rejected if the trace test statistic is greater than the critical value. The same test is conducted for r = 1, r = 2,…, r = K in that order. The cointegration rank, r, is determined by the first test for which one fails to reject the null hypothesis (i.e., the trace test statistic is less than the critical value). See Juselius (2006) for a detailed explanation of the trace test.

Post-Estimation Procedures

Lütkepohl (2004b) outlines the eigenvalue problem which can be used to solve for $\hat{\beta}$ and $\hat{\alpha}$. These parameters yield the estimated coefficients, $\widehat{\Pi} = \hat{\alpha}\widehat{\beta}'$. Restrictions can be placed on matrices $\hat{\alpha}$ and $\hat{\beta}$ to test various hypotheses. The variable exclusion test is performed by testing the hypothesis of a zero row of $\hat{\beta}$. Failure to reject the null hypothesis leads to the conclusion that the variable in question is not in the long-run relationships. Hypothesis tests on $\hat{\alpha}$ are conducted to determine short-run adjustment to perturbations in the long-run relation, weak exogeneity of variables. The hypothesis of this test is that a variable impacts the long-run trends of other variables (Juselius 2006). Additionally, VECM post-estimation procedures include testing for stationarity of individual variables within the VECM.

Innovation accounting (impulse response functions and forecast error variance decomposition) is conducted to observe the individual responses of each variable in the system to a one-time shock in each other variable. The VECM is converted to its equivalent levels VAR to conduct innovation accounting.

Before innovation accounting can be conducted, however, the residuals of the model have to be orthogonal, or contemporaneously uncorrelated. Uncorrelated residuals are necessary so the reaction of the variables to a shock in only one other variable can be observed. Correlated residuals mean that shocks to variables are not independent, so that variables experience contemporaneous shocks. In the case of correlated residuals, impulse responses may not represent the true causal relationship between the variables (Lütkepohl 2005).

VECM residuals for economic data are rarely uncorrelated (Juselius 2006). A Bernanke ordering is one method for orthogonalizing the residuals (Bernanke 1986). As described in Chopra and Bessler (2005), Bernanke ordering consists of using the VECM estimates to write the vector of innovations as $e_t = H^{-1}v_t$, where *H* is a K×K matrix and v_t is a K×1 vector of orthogonal shocks. The residuals from the VECM estimation are used to obtain directed graphs, which provide the *H* matrix. The VECM equivalent-levels VAR is multiplied by *H* to perform innovation accounting.

Directed acyclic graphs (DAGs) represent causal relationships among variables. TETRAD IV is a computer program used to search for causal relationships between variables and build a corresponding DAG (Awokuse and Bessler 2003). In a directed acyclic graph, all causal links between variables have directed edges and there are no cycles among the variables (i.e., no circular causal paths). Series A (independent of the *A* matrix noted in equations 2 and 3 above) is known as a "parent" of series B if a directed edge runs from A to B (A→B). This directed edge indicates that A causes B (Spirtes, Glymour, and Scheines 2000). Additionally, Spirtes, Glymour, and Scheines (2000) describe the relationship between A and B within a DAG as follows:

> "For any directed acyclic graph *G* and for any probability distribution *P* satisfying the Markov and Minimality Conditions, if variables *A* and *B* are statistically dependent, then either: (i) there is a directed path in *G* from *A* to *B*; or (ii) there is a directed path in *G* from *B* to *A*; or (iii) there is a variable *C* and

> directed paths in *G* from *C* to *B* and from *C* to *A*" (Spirtes, Glymour, and Scheines 2000, p. 12).

Undirected edges between two variables A and B (A − B) indicate that the causality between the variables cannot be verified, but that A and B are related.

The PC algorithm is one method for determining directed graphs. PC algorithm, described in Spirtes, Glymour, and Scheines (2000), begins with a complete undirected graph. It proceeds by removing edges between variables based on conditional independence. The remaining undirected edges are then oriented so that they become directed. PC algorithm, however, assumes that there are no latent variables which may be affecting those variables included in the model. The Fast Causal Inference (FCI) algorithm, adapted from the PC algorithm, does not assume that there are no latent variables (Haigh and Bessler 2004). The graph output of the FCI algorithm is considered a partially oriented inducing path graph. As such, it can have several edges: A →B, A ←B, A o-o B, A o→B, A ←o B, or A ←→B. In the case that A o-o B, then the edge can be either A → B, A ←→B, or A←B. FCI begins in the same manner as the PC algorithm, by beginning with a completely undirected graph and then removing an edge between two variables if they are dependence-separated. It then orients the remaining edges as A o-o B. The next step is to replace "o" with "→" if possible to form directed edges (Spirtes, Glymour, and Scheines 2000).

Greedy Equivalence Search (GES) is a third algorithm that can be used to search for patterns among variables in TETRAD. GES works to obtain the pattern's score by first attempting to add edges that would increase the score then working backwards to remove edges so as to further increase the score. The algorithm stops when it can no longer remove edges to increase the pattern's score (Chickering 2002; Glymour et al. 2004). The PC, FCI, and GES algorithms are all examined to determine potential Bernanke orderings.

Another method that is used to obtain uncorrelated residuals for impulse response functions is a Choleski decomposition of the innovation covariance matrix. This method requires that the order of the variables in the system be specified. The specification is such that the first variable has a potential impact on all of the other variables; the second has a potential impact on all of the variables besides the first, and so on in contemporaneous time (Lütkepohl 2005). A Bernanke ordering, via the directed graph, is used to orthogonalize the residuals rather than a Choleski decomposition, because the ordering of system variables for a Choleski must be determined by the researcher, while the Bernanke ordering is obtained using information found in the data.

CHAPTER IV

RESULTS

Stationarity Test Results

The results of the Augmented Dickey-Fuller (ADF) tests are shown in table 4.1. The ADF test for zero to 11 lags is used to determine whether each of the individual logged series is stationary, meaning that the series tends to return to its long-run average. None of the levels series are stationary at the 5% significance level, because the t-test values for the coefficients of the lagged prices are not less than the critical value for the 5% significance level. As provided in Fuller (1996), the critical value for the 5% significance level is -2.86. All first differences of the series, however, are stationary at the 5% significance level, suggesting that the use of a VECM may be appropriate.

Model Specification

The lag number of the model is determined before the cointegration rank is determined; therefore, the lag number for the VAR form of the model is determined rather than that of the VECM (Lütkepohl 2004b). Values for the Schwartz Information, Akaike Information, and Hannan and Quinn criteria for lags zero to 11 are reported in table 4.2. Two of the three criteria, the Schwartz Information Criterion and the Hannon and Quinn Criterion, are minimized at one lag. The Akaike Criterion, minimized at 11 lags, tends to overestimate the lag order in comparison to the other two loss criteria (Lütkepohl 2004b). One lag, therefore, is chosen for the VAR model as suggested by the Schwartz Information and Hannon and Quinn criteria.

Table 4.1. Augmented Dickey-Fuller Test for Stationarity using Natural Logarithmic Series

Series	t-test[a]	SIC[b]	Lags(k)	H&Q[b]	Lags(k)
			Levels		
Crude Oil	-1.45	-4.83	1	-4.87	1
Gasoline	-1.46	-5.47	2	-5.52	2
Corn	-1.04	-5.12	1	-5.16	1
Food CPI	0.15 (-0.01)[c]	-11.91	1	-11.96	3
Ethanol	-1.85	-4.87	2	-4.92	2
Food PPI	0.04	-9.39	1	-9.43	1
Fuel PPI	-1.17	-5.82	1	-5.86	1
Dollar Index	-1.16	-8.73	1	-8.76	1
			First Differences		
Crude Oil	-8.72*	-4.86	0	-4.88	0
Gasoline	-8.17*	-5.50	1	-5.54	1
Corn	-8.25*	-5.16	0	-5.18	0
Food CPI	-9.02* (-4.46*)[c]	-11.96	0	-11.99	2
Ethanol	-9.02*	-4.88	1	-4.92	1
Food PPI	-8.32*	-9.43	0	-9.46	0
Fuel PPI	-9.40*	-5.85	0	-5.88	0
Dollar Index	-7.64*	-8.76	0	-8.79	0

a) The t-test statistic is associated with the lagged coefficient of the given price series variable. In the Augmented Dickey-Fuller test, this t-test statistic is compared to the ADF critical values. The critical value is -2.86 for the 5% significance level (Fuller 1996). The t-test values correspond to the number of lags given by the minimum SIC and H&Q values. The * marks significance at the 5% level, meaning that the series is stationary.

b) SIC is the Schwartz Information Criterion. H&Q is the Hannan and Quinn Criterion. SIC = log(seesq) + nreg × log(N)/N and H&Q = log(seesq) + 2.01 × nreg × log(log(N))/N, where seesq is the estimated variance of the error, nreg is the number of regressors, and N is the number of observations. Zero to 11 lags were used for the ADF test. The number of lags enumerated above corresponds to either the minimum SIC or minimum H&Q value for each data series.

c) If two t-test statistics are given, the value in parentheses corresponds to the minimum H&Q value, while the other to the minimum SIC.

A VECM may be more suitable for the modeling process than a VAR model, because all variables are non-stationary in levels but stationary in first differences, indicating the possibility of cointegrating relationships. The trace test, for both a restricted and an unrestricted constant, is used to determine the cointegration rank for estimation of the VECM. Trace test results are given in table 4.3; the process for

Table 4.2. Lag Order Determination for a Levels VAR Model[a]

Lags	SIC[b]	AIC[b]	H&Q[b]
0	-41.81	-42.11	-41.92
1*	-57.74	-59.37	-58.66
2	-56.87	-59.84	-58.60
3	-55.36	-60.67	-57.90
4	-53.89	-60.54	-57.25
5	-52.35	-60.34	-56.52
6	-51.09	-60.42	-56.08
7	-49.59	-60.26	-55.39
8	-48.37	-60.38	-54.98
9	-47.47	-60.81	-54.89
10	-46.41	-61.09	-54.65
11	-45.97	-62.00	-55.03

a) Logged series data are used for each test. The * marks the number of lags used in the model.

b) SIC is the Schwartz Information Criterion. AIC is the Akaike Information Criterion. H&Q is the Hannan and Quinn Criterion. SIC = log det($\sum_u$) + (nreg×K) × (log(N))/N; AIC = log det($\sum_u$) + 2 × (nreg×K)/N; and H&Q = log det($\sum_u$) + 2.01 × (nreg×K) × log(log(N))/N, where det($\sum_u$) is the determinant of the residual covariance matrix, nreg is the number of regressors in the model, K is the number of series in the model, and N is the number of observations. To find the appropriate number of lags for each model, zero to 11 lags were used in each test.

Table 4.3. Trace Test for Cointegration Rank with One Lag in the VAR[a]

		Restricted Constant		Unrestricted Constant	
K-r	r	Trace	C (5%)	Trace	C (5%)
8	0	319.32	169.41	232.61	159.32
7	1	179.24	134.54	162.70	125.42
6	2	119.20	103.68	104.05	95.51
5	3*	82.88	76.81	67.87*	69.61
4	4	47.22	53.94	33.45	47.71
3	5	28.23	35.07	16.77	29.80

a) The trace test, performed with both a restricted and an unrestricted constant, is used to determine the cointegration rank for each dataset. "K-r" is the number of unit roots where K is the number of series in the model, "r" is the cointegration rank, and "Trace" is the test statistic associated with the rank in the second column of the table. "C(5%)", critical values for both a restricted constant and an unrestricted constant at the 5% significance level, are from Juselius (2006), Appendix A: Case 2 and Case 3 (p.420). The table is read from left to right, from restricted constant to unrestricted, then down, from the highest K-r value to the lowest, in determining the cointegration rank. The null hypothesis is that there are at least K-r unit roots. The cointegration rank is at the first occurrence in which the corresponding Trace test statistic is less than C(5%), the first instance in which one fails to reject the null hypothesis (Juselius, 2006). This cointegration rank, as well as, the first trace test statistic that is lower than C(5%), are marked by *.

determining the cointegration rank is explained in the table. The trace test indicates that the appropriate VECM has a cointegration rank of three with an unrestricted constant.

Stationarity, Weak Exogeneity, and Exclusion Tests in the Cointegration Space

Once the cointegration rank is determined, stationarity tests are performed to check the stationarity of each of the logged price series in the VECM (table 4.4). The null hypothesis of stationarity is rejected for each series. While these stationarity tests are different from the ADF tests including having a different null hypothesis, inferences from these tests support the results of the ADF tests.

Tests of weak exogeneity are used to determine the series which drive the long-run trends of the other series. The null of weak exogeneity is rejected for all eight series at the 5% significance level, indicating that all eight series work to bring the system back into equilibrium following a shock (table 4.4).

The exclusion test's null hypothesis is that a series can be excluded and is "…not needed in the cointegration space" (Juselius 2006, p. 176). At the 5% significance level, the test's null hypothesis is failed to be rejected for the crude oil, gasoline, food CPI, ethanol, and food PPI variables (table 4.4), indicating that these variables are not in the long-run relationships. The null hypothesis is rejected for all of the remaining variables: corn, fuel PPI, and the dollar index. If the significance level is 10%, the null hypothesis of exclusion would only be rejected for crude oil and food CPI. Juselius (2006) cautions that the null of exclusion may not be rejected in the case that two or more series are strongly correlated even if a series is in one or more of the long-run relations. Note the correlation coefficients, calculated using non-logged data values, between those series

Table 4.4. Post-Estimation Tests Conducted on the VECM

Series	Stationarity[a]		Weak Exogeneity[b]		Exclusion[c]	
	Chi-Square	P-value	Chi-Square	P-value	Chi-Square	P-value
Crude Oil	31.960	0.000	7.889	0.048	6.734	0.081*
Gasoline	30.150	0.000	18.868	0.000	2.673	0.445**
Corn	35.007	0.000	9.504	0.023	16.126	0.001
Food CPI	35.211	0.000	29.243	0.000	6.765	0.080*
Ethanol	30.147	0.000	10.281	0.016	0.204	0.977**
Food PPI	34.866	0.000	21.992	0.000	3.934	0.269**
Fuel PPI	33.474	0.000	23.099	0.000	8.878	0.031
Dollar Index	33.471	0.000	12.636	0.005	8.689	0.034

a) The null hypothesis of the stationarity test is that the logarithms of the series, where each series is a vector in the cointegration space, are stationary (Juselius 2006). The p-values given in the right-hand column show that the null of stationarity is strongly rejected for each logged price and index series.

b) The null hypothesis of the weak exogeneity test is that a given logged series is weakly exogeneous in the long-run, meaning that "…a variable has influenced the long-run stochastic path of the other variables of the system, while at the same time has not been influenced by them…" (Juselius 2006, p. 193). No variables were found to be weakly exogenous at the 5% significance level.

c) The failure to reject the null hypothesis means that the given logged series can be excluded (Juselius 2006). The * mark the p-values of those series which are not needed in the cointegration space at the 5% significance level, while the ** mark those not needed at the 10% significance level.

for which exclusion is not rejected: crude oil and gasoline (0.97), gasoline and ethanol (0.86), and food CPI and food PPI (0.98). These correlation coefficients indicate that one or more of these series may be in the long-run relationships.

Directed Graph

The correlation matrix of the VECM residuals (table 4.5) is used via TETRAD IV to obtain a directed acyclic graph (DAG). Only three values in the residual correlation matrix are greater than the absolute value of 0.4. Seven values are greater than the absolute value of 0.3. As discussed in the methodology, a Bernanke ordering uses the directed graph to orthogonalize the residuals, a crucial step in obtaining impulse response functions.

Table 4.5. Residual Correlation Matrix of the VECM

	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
Crude Oil	1.000							
Gasoline	0.665	1.000						
Corn	0.124	-0.036	1.000					
Food CPI	-0.005	-0.003	0.067	1.000				
Ethanol	0.229	0.381	0.064	-0.014	1.000			
Food PPI	0.213	0.215	0.273	0.189	0.173	1.000		
Fuel PPI	0.675	0.769	0.016	0.078	0.318	0.202	1.000	
Dollar Index	-0.387	-0.265	-0.288	-0.015	-0.107	-0.194	-0.365	1.000

Three different algorithms - PC, GES, and FCI - were initially used within TETRAD to obtain directed graphs. The PC algorithm gave the "best" directed graphs in the context that it is able to identify the direction of more relationships between the series than either the GES or FCI algorithms. The directed graph ultimately used to orthogonalize the VECM residuals, therefore, is that based on the PC algorithm. It should be noted that use of the PC algorithm requires the assumption that there are no latent variables influencing the system.

Employing the PC algorithm with an alpha equal to 0.05 in TETRAD gives the DAG depicted in figure 4.1, which shows four directed edges and four undirected edges. There are eight possible DAGs given that there are four undirected edges and that no cycles can exist among the variables. Increasing the alpha level did not reduce the number of undirected edges. Impulse response functions and forecast error variance decompositions are obtained using each of the eight DAGs. Although there are some differences among the innovation accounting results based on the different DAGs, inferences from the results are similar. Hence, only one of the eight DAGs and the

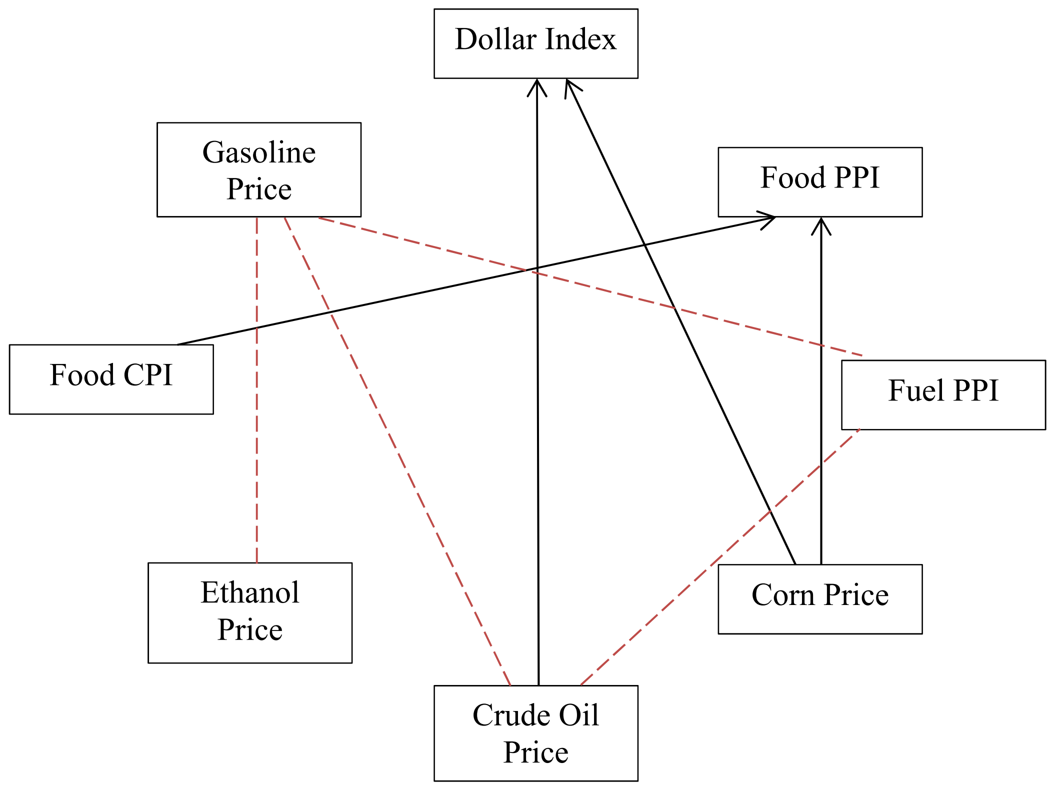

Figure 4.1. Directed Acyclic Graph Generated by PC Algorithm with Alpha Equal to 0.05. The DAG Has Four Directed and Four Undirected Edges. Orientation of the Undirected Edges Gives Eight Possible DAGs for Describing the Contemporaneous Relationships among the Series

innovation accounting results based on this DAG are presented in the text of this thesis. The remaining seven DAGs and associated impulse response functions and forecast error variance decompositions are presented in the appendices.

The directed graph employed in the innovation accounting procedures is depicted in figure 4.2. This DAG has the following causal structures for the undetermined edges: gasoline causes ethanol price, crude oil causes gasoline, crude oil causes fuel PPI, and

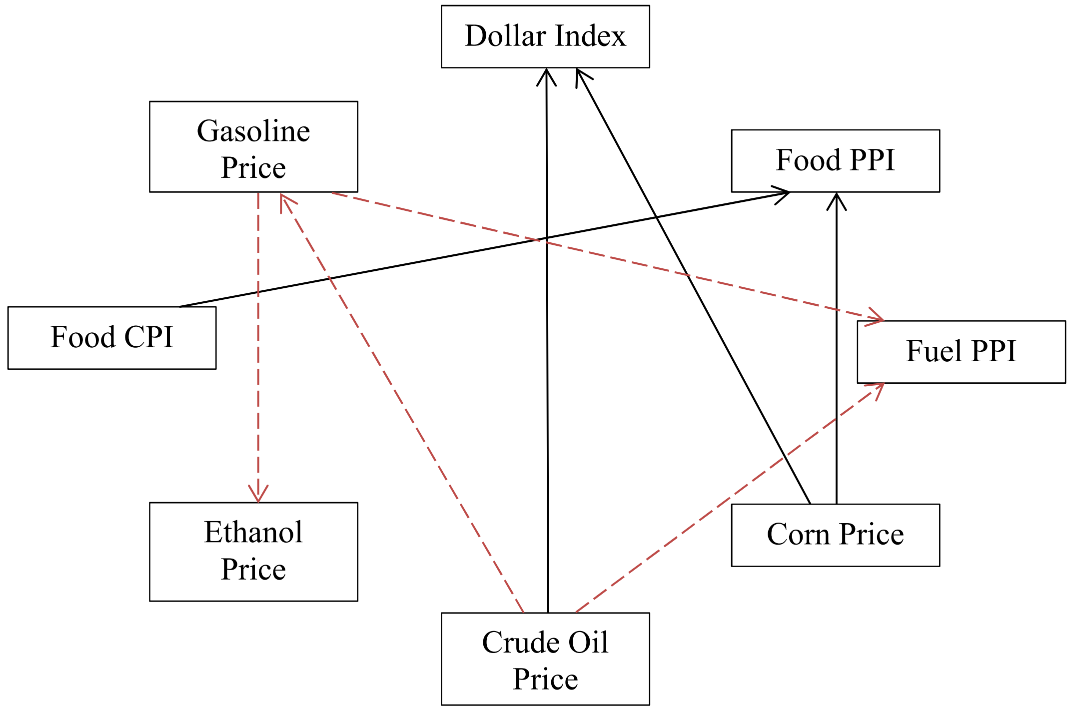

Figure 4.2. DAG used in the Innovation Accounting Procedures

gasoline causes fuel PPI. Economic reasoning and previously published research used to select this DAG are discussed in succeeding paragraphs. It should be noted that results from these previous studies are not contemporaneous time results as needed to create the DAG; no such results were found in the literature. These studies are used with this limitation in mind.

Causal Relationship: Crude Oil and Gasoline Prices

Given that there are four undirected edges in the directed graph, four causal relationships need to be determined to obtain a fully oriented graph for residual orthogonalization. The assumption that crude oil price causes gasoline price for the period of study, January

2000 through February 2012, is demarcated by an arrow oriented from crude oil to gasoline. Conclusions from previous studies, as well as, information regarding gasoline production led to the crude oil to gasoline causal relationship. Kilian (2010) determines that increases in U.S. gasoline prices between 2002 and 2008 can mostly be attributed to the growing global demand for commodities, including crude oil. Hamilton (2008) and Kilian and Murphy (2011) identify the global increase in the demand for crude oil as the main contributor to high crude oil prices for much of the last decade. Persistent increases in global demand for crude oil will drive up its price. Given that crude oil is the major input into gasoline production (EIA 2009), increases in the price of crude oil should lead to an increase in the price of gasoline as producers require higher prices to produce any given quantity. Additionally, Kilian (2010) attributes the decline in gasoline prices beginning in late 2008 to the decline in world oil demand.

Observations regarding how gasoline responds to demand shocks provide additional support for the crude oil to gasoline relationship. While demand shocks for gasoline affect crude oil prices, such shocks are not sizeable or frequent enough to reverse the causal relationship of crude oil price to gasoline price. Although shocks to refinery capacity (supply shocks) reduced U.S gasoline supply following Hurricanes Rita and Katrina in 2005 and most likely led to temporarily reduced demand for crude oil, these effects were fleeting compared to the persistent increases in the demand for crude oil which drove up gasoline prices for much of the 2000s (Kilian 2010). Further, Hughes, Knittel, and Sperling (2007) found that U.S. consumers short-run price elasticity of demand for gasoline was between -0.034 to -0.077 for 2001 to 2006. U.S.

consumers, therefore, are not very responsive to gasoline price increases, resulting in little change in the U.S. demand for crude oil as gasoline prices increase. Also, because crude oil is used to produce many products in addition to gasoline, effects of shocks to gasoline demand are dampened in their effects on the crude oil market. Considering all of these studies and points, the assumption is made that for the time period studied, crude oil price causes gasoline price.

Causal Relationship: Gasoline and Ethanol Prices

Next, the orientation of the edge between gasoline price and ethanol price has to be determined. Both the ethanol blend wall and the Renewable Fuel Standard (RFS) were considered before the edge was oriented such that gasoline price causes ethanol price. In the event that the RFS mandates requiring specified quantities of biofuel production did not exist, changes in ethanol supply would be caused by changes in production costs and changes in ethanol demand associated with the profitability of blending ethanol into gasoline. Gasoline price increases make it more profitable to blend-in ethanol, causing an increase in the demand for and the price of ethanol (Meyer and Paulson 2012). In support of this statement, McPhail, Westcott, and Lutman (2011) posit that, as crude oil prices rise, fuel producers usually increase the amount that they are willing to pay for substitute biofuels, such as ethanol.

In theory, the demand curve for ethanol is perfectly inelastic at the RFS mandated level for ethanol (Q_M) (see figure 4.3 – solid demand curve line). If the market produces more ethanol than the RFS mandated level, then the ethanol price and quantity is determined by the market (intersection of dashed demand curve and supply

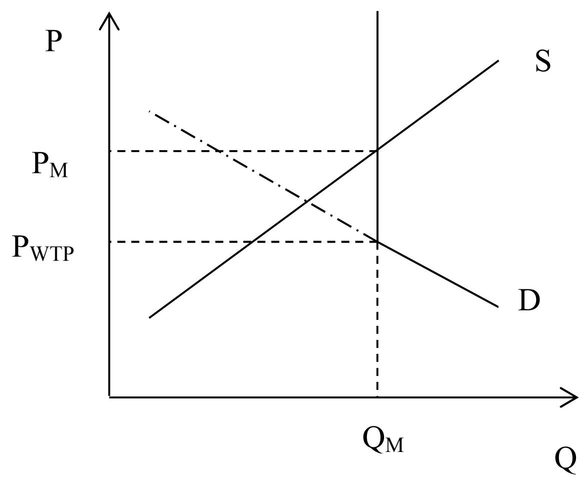

Figure 4.3. Ethanol Market under a Binding RFS Mandate

curve), just as if no RFS mandate existed. If the market, however, produces the RFS mandated quantity, then the RFS is binding and there is a gap between the price that the producer is willing to accept for the mandated quantity (P_M) and the price consumers are willing to pay (P_{WTP}) (Meyer and Paulson 2012).

In the case in which the ethanol mandate is binding, the quantity of ethanol produced for fuel is determined by the mandate and not by profitability. So, it is imperative to the question of causal relationship between gasoline and ethanol prices to know whether the RFS mandate is binding or not. If it is binding, it is likely that ethanol price causes gasoline price; however, if the mandate is not binding, then gasoline price likely drives ethanol price. The RFS mandates did not take effect until 2006; thus, in the early years of the period studied in this thesis it is likely there was a gasoline to ethanol causal relationship.

Production of ethanol for fuel blending surpassed the RFS mandated levels in each year from 2006 to 2010 (McPhail, Westcott, and Lutman 2011), suggesting the RFS was likely not binding. Abbott, Hurt, and Tyner (2009) speculate that the RFS was binding for the first time at the end of 2008 as a result of ethanol plant shutdowns. As production, however, was again above the RFS in 2009, the RFS mandate was likely not binding for long. McPhail, Westcott, and Lutman (2011) also reason that the RFS mandate was not binding for 2011 because of the low price of Renewable Identification Numbers, which correspond to volumes of renewable fuel and can be used to meet fuel blender's RFS requirements or sold to another blender so that they can meet theirs.

Another limit to ethanol market growth is the ethanol blend wall. Under U.S. law during the study period, the maximum volume of ethanol allowed in conventional gasoline is 10%. If every gallon of conventional gasoline contains 10% ethanol by volume, then the ethanol market has hit the blend wall; the domestic market cannot use any additional ethanol. The EIA estimates that the U.S. reached this blend wall in June 2011 (EIA 2011b). Only the final few months of the study period, therefore, are potentially affected by the blend wall.

In summary, before the RFS was enacted in 2006, gasoline prices may have caused ethanol prices because use of ethanol was driven by profitability; higher gasoline prices increased the demand for ethanol. After 2006, gasoline prices may have caused ethanol prices because: (1) the RFS was found to be non-binding for 2006 through 2011; and (2) the ethanol blend wall was not a factor in constraining ethanol production for nearly all of the study period. A non-binding RFS and ethanol production below the blend wall imply that the price and quantity of ethanol is determined by the market. Demand for ethanol would be driven by profitability given the price of gasoline, i.e., gasoline price causes ethanol price.

Causal Relationships: Crude Oil, Gasoline, and Fuel PPI

Finally, the edges between fuel PPI and crude oil and between fuel PPI and gasoline must be oriented. The edge between fuel PPI and crude oil is directed such that crude oil causes fuel PPI. Fuel PPI represents the changes over time in prices received by producers for their products. Many products included in this index are produced using crude oil, including gasoline, kerosene, jet fuels, heating oil, diesel fuel, and residual oils. It is assumed that producers consider their production costs when contemplating the prices they are willing to accept for their products and that the price of crude oil would influence these sale prices. Additionally, this conclusion is consistent with the directed edge oriented by the PC algorithm in which corn (also an input to production) causes food PPI.

The edge between gasoline and fuel PPI was oriented such that gasoline (output) causes fuel PPI (proxy for costs). This edge orientation is consistent with the relationship of food CPI (output) causing food PPI (proxy for costs) defined by the PC algorithm.

Impulse Response Functions

Graphs of the impulse response functions show the responses of each series to a one-time shock to each of the other series. In figure 4.4, the first column of graphs shows the responses of each series to an innovation (shock) to crude oil. The second column

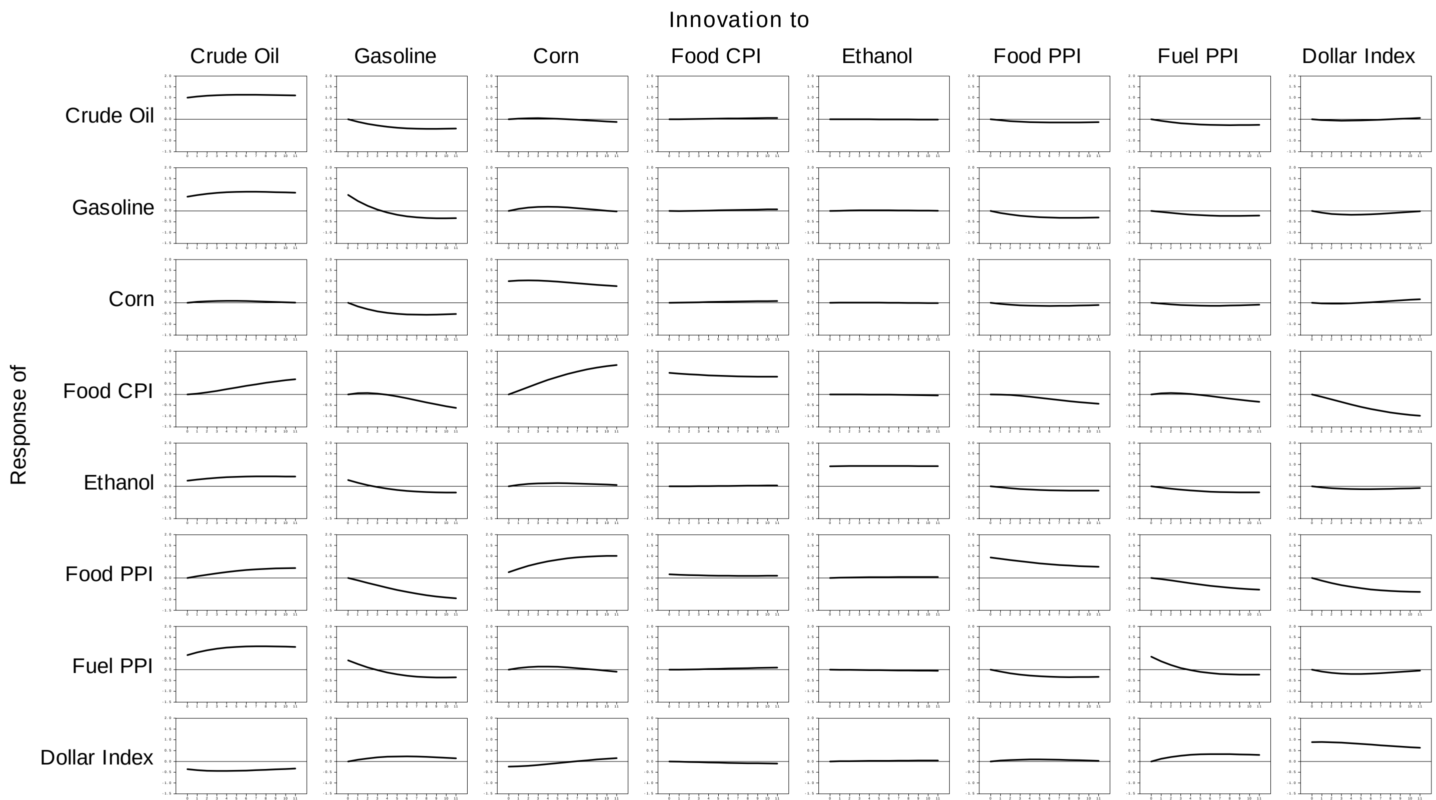

Figure 4.4. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series

shows the response of each series to a shock in gasoline, and so on. The series are measured in different units. To allow for comparison among the series, the impulses are scaled by dividing the impulse response for each series by their standard deviation of the residuals.

All series, except the dollar index, react positively to a shock to crude oil prices. The responses of crude oil, gasoline, ethanol, and fuel PPI are immediate and permanent. Scaled responses, however, differ in their magnitudes with that of ethanol being the smallest of the four. Corn's response to crude oil is positive but small. Food CPI responds gradually to a shock to crude oil. Unlike the other series, however, food CPI continues to increase and stabilizes slowly. The dollar index reacts negatively and immediately to an innovation in crude oil prices. Consequently, the negative response of the dollar index to crude oil indicates that these series move in opposite directions.

Responses to gasoline price shocks tend to be negative with the exclusion of gasoline, ethanol, and fuel PPI. Gasoline, ethanol, and fuel PPI react immediately and positively, but each falls back to its initial level after approximately three periods. The response of food CPI, while initially slightly positive, becomes rapidly negative after only a few periods.

Crude oil, gasoline, and ethanol responses to a shock in corn prices are positive, but small. The reaction of corn is large, positive, and immediate. Food CPI and food PPI display large, positive responses; these responses increase over time but at decreasing rates. While the response of food PPI to a shock to corn levels out at longer horizons, the rate of change in the response of food CPI does not decrease as quickly as that of food PPI. Furthermore, the scaled response of food CPI to a corn shock is the largest in magnitude among its responses to shocks to any other series.

As expected, food CPI and ethanol both respond positively, immediately, and permanently to their own shocks. No other series, however, has much of a response to shocks in either food CPI or ethanol.

Responses to an innovation to food PPI are predominantly small and negative, but tend to level out in the longer term. Food PPI and the dollar index, however, both react positively to a shock in food PPI. Whereas, the response of the dollar index is small, the response of food PPI is large but decreases over time.

A shock to fuel PPI elicits responses from all series, most of which are negative. Fuel PPI has a positive, immediate response at the time of innovation, but falls over time. The dollar index also responds positively; the magnitude of the response is small and grows for about four periods before leveling out. Crude oil, gasoline, and ethanol responses initially decrease, but also level out after approximately four periods. The negative response of food PPI levels out more slowly.

Finally, except for its own response, the responses of all series to a shock to the dollar index are negative. Crude oil, gasoline, corn, ethanol, and fuel PPI scaled responses are very small, while those of food CPI, food PPI, and the dollar index are larger in magnitude. The response of the dollar index to its own innovation is positive and immediate. The responses of food CPI and food PPI, though, are large, negative, and decreasing, with the response of food PPI leveling out more rapidly than that of food CPI.

Forecast Error Variance Decompositions

Forecast error variance decompositions (table 4.6) provide estimates of the extent to which a series can be explained by information in itself and the other series. In the table, the percentage of variation in each series attributed to information in itself and the other series at specified horizons is given. The first four numerical rows of table 4.6, for example, give the forecast error variance for crude oil at the horizons 0, 1, 5, and 11. In contemporaneous time (horizon zero), 100% of the uncertainty (price variation) in crude oil prices comes from innovations to its own prices. Alternatively stated, no other series provide information to crude price in contemporaneous time. This result is expected, because in the DAG, no series explains crude oil in contemporaneous time.

Forecast error variance for crude oil remains largely attributable to innovations to itself throughout the horizons. At horizon 11, crude oil still accounts for nearly 86% of its own variation. Most of the remainder of crude oil variation at horizon 11 is because of gasoline (9%). Fuel PPI provides some information to crude oil price, explaining approximately 3% of crude oil's variability at horizon 11.

In contemporaneous time, crude oil and gasoline provide all the information to gasoline price, explaining approximately 44% and 56% of variation in gasoline price. Gasoline's variation attributable to crude increases at longer term horizons, growing to 73%. Gasoline variation attributable to itself shrinks to about 13% by horizon 11. The large contribution of crude oil to gasoline variation suggests that crude oil is an important factor in gasoline price determination. Food PPI and fuel PPI start to provide some information to gasoline by the 5th horizon.

Table 4.6. Decomposition of Forecast Error Variance for Each of Eight Series

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	98.87	0.66	0.05	0.00	0.00	0.10	0.26	0.06
5	91.43	5.40	0.10	0.02	0.00	0.76	2.09	0.19
11	85.91	9.11	0.25	0.09	0.01	1.09	3.41	0.13
				Gasoline				
0	44.22	55.78	0.00	0.00	0.00	0.00	0.00	0.00
1	55.25	43.24	0.57	0.00	0.01	0.46	0.09	0.38
5	72.59	16.38	2.77	0.02	0.06	4.36	1.72	2.10
11	73.44	12.67	1.77	0.21	0.06	7.00	3.37	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.08	1.39	98.27	0.00	0.00	0.14	0.08	0.04
5	0.39	10.81	87.03	0.05	0.00	0.92	0.74	0.06
11	0.31	18.75	77.86	0.22	0.01	1.26	1.06	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.08	0.17	1.47	97.53	0.00	0.00	0.13	0.63
5	2.62	0.24	19.89	67.06	0.00	0.52	0.14	9.55
11	7.49	4.01	34.81	32.30	0.02	2.46	1.17	17.75
				Ethanol				
0	6.42	8.10	0.00	0.00	85.48	0.00	0.00	0.00
1	8.00	5.27	0.19	0.00	86.07	0.13	0.19	0.15
5	12.25	2.36	1.10	0.00	79.94	1.27	2.09	0.98
11	14.17	4.17	0.96	0.03	73.16	2.28	4.22	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	0.29	0.63	12.13	2.58	0.01	83.45	0.14	0.78
5	3.11	8.62	28.58	1.33	0.04	48.64	2.49	7.18
11	5.42	19.35	33.08	0.69	0.06	23.98	6.14	11.29
				Fuel PPI				
0	45.56	18.37	0.00	0.00	0.00	0.00	36.06	0.00
1	58.43	13.37	0.30	0.00	0.00	0.45	27.05	0.40
5	78.44	5.14	1.23	0.04	0.02	4.01	8.94	2.17
11	78.83	6.78	0.71	0.25	0.07	6.23	5.57	1.56
				Dollar Index				
0	13.01	0.00	6.07	0.00	0.00	0.00	0.00	80.92
1	14.33	0.31	5.54	0.01	0.00	0.07	0.70	79.03
5	16.80	2.53	3.21	0.12	0.03	0.44	5.20	71.68
11	17.28	3.52	2.27	0.45	0.09	0.45	8.64	67.31

Corn and ethanol prices explain nearly all of their own price variation at the first two horizons. Even at the 11th horizon, these markets are responsible for the majority of their own forecast error variance with corn still contributing over 77% and ethanol over 73% of their own variation. Gasoline explains most of the remaining variation in corn price, with variance contributions growing from 0% in contemporaneous time to approximately 19% at horizon 11. Crude oil, with the exception of ethanol itself, contributes the most of any other series to the uncertainty in ethanol prices, providing an estimated 6% of variation at horizon 0 and growing to over 14% at horizon 11. Gasoline, too, provides information to ethanol price, explaining approximately 8% of variation in contemporaneous time, but decreases in importance by approximately one-half at the 11th horizon.

In nearer term horizons, food CPI's forecast error variance is attributed to information discovered in its own series. Crude oil, corn, and the dollar index are important in explaining food CPI in the longer horizons. At horizon 11, crude oil, corn, food CPI, and the dollar index's percentage contributions to food CPI uncertainty are 7%, 35%, 32%, and 18%. The decompositions for food PPI closely resemble those for food CPI. As occurred with food CPI, the percentage of food PPI explained by itself falls over time, while the importance of the other series increases. One difference between food CPI and food PPI is that the information provided by corn prices increases more rapidly for the food PPI than for the food CPI, although by the 11th horizon the percentage variations are roughly equal at around 33 - 34%.

Finally, crude oil contributes to the percentage variance of both fuel PPI and the dollar index at all horizons. Crude oil's contribution to fuel PPI variance is 46% at horizon 0 and increases to over 75% 11 periods out. Most of the remainder of the variance in fuel PPI comes from innovations to itself and gasoline; as the variance attributed to crude oil grows, the contributions by itself and gasoline fall. The dollar index explains the majority of its forecast variance at all horizons with crude oil contributing between 13% and 17%. At the 11th horizon, gasoline, corn, and fuel PPI explain at least two percent of the variation in the dollar index.

Discussion

Results suggest that crude oil price is an important factor in determining all series in the system, as it accounts for at least five percent of the forecast error variance at the 11th horizon for all series except corn. Crude oil's largest information contributions to series other than itself are to gasoline price and fuel PPI. This result is expected in the short run, because crude oil price explains both gasoline and fuel PPI in the DAG. Furthermore, crude oil's percentage of each series' forecast error variance, other than its own, increases as the horizon increases.

As to the impulse response functions, a shock to crude oil elicits positive responses from every series other than the dollar index. Because crude oil is an input into gasoline and other fuels used to produce and transport both corn and food, these positive responses are expected. Ethanol response, which rises in response to a shock in crude oil, supports the view of McPhail, Westcott, and Lutman (2011) that crude oil price increases may result in increases in the price fuel producers are willing to pay for substitute biofuels, including ethanol. Furthermore, the negative response of the dollar index to a shock to crude oil price is also anticipated. The rising price of imported crude oil increases the U.S. trade deficit and results in a downward adjustment in the value of the U.S. dollar (Feldstein 2008).

Ethanol price shows an immediate positive response to a shock to gasoline price (expected given the DAG), suggesting that a jump in gasoline price does increase the demand for ethanol at least initially. This scaled response of ethanol is smaller than its response to a shock to crude oil and decreases over time. Gasoline provides more information to ethanol price in the early horizons than the middle and late horizons.

The contribution of information from corn price to food CPI and food PPI is not surprising, because corn is an input to many processed food items and animal feed. As depicted in the impulse response functions, a shock to corn price leads to an increasing food CPI and food PPI as the costs of processed foods, dairy products, and meat rise. An approximately 7% increase in corn price leads to an estimated 0.3% increase in food CPI over one year. Additionally, very little of the variation in gasoline and ethanol price is because of information from corn price. Corn contributes less than 3% to the forecast error variance of gasoline and just more than 1% to ethanol at any of the 11 horizons. This result is consistent with gasoline explaining ethanol in the DAG which suggests that ethanol demand is driven by profitability dependent upon the price of gasoline. The price of ethanol is more attributable to the price of gasoline than to the price of its input, corn.

The dollar index, like corn price, provides information to both the food CPI and the food PPI at the later horizons, indicating that the relative exchange rate of the U.S. dollar may affect food prices. In contrast, ethanol does not provide much information to food CPI, food PPI, or corn price. Ethanol explains less than 0.1% of the uncertainty in any of these series, suggesting that ethanol price is not a major contributor to food price variability. Together, crude oil prices, corn prices, and the relative exchange rate of the U.S. dollar appear to be the most informative factors in determining food prices, with greater influence in the longer horizons than in the shorter ones.

Comparison of Results from Other DAGs

As noted earlier, the innovation accounting results from the eight different DAGs, although showing many similarities, are different in some respects. Differences, which are small, are discussed here. The innovation accounting results are generally robust to the DAG specification. The DAGs, impulse response functions, and forecast error variance decompositions for the seven cases not presented in the text are documented in the appendices. DAGs 1 and 3 (see Appendices A, B, and C) both share the crude oil to gasoline and gasoline to ethanol causal relationships with the DAG presented in the text (selected DAG). The only difference between DAG 1 and the selected DAG is the direction of the contemporaneous relationship between gasoline and fuel PPI, namely fuel PPI explains gasoline in DAG 1 rather than the other way around. With fuel PPI explaining gasoline, the scaled responses of all series to a shock in gasoline price are slightly smaller in magnitude than the responses from the selected DAG results, while those of fuel PPI are larger. Similarly, the forecast error variances for each series attributed to fuel PPI increase in proportion to the decrease in the variances attributed to gasoline.

DAG 3 differs from the selected DAG in that fuel PPI explains crude oil and gasoline rather than being explained by them. Consequently, crude oil provides less information to itself, gasoline price, and fuel PPI, while fuel PPI provides more, at every horizon than in the results for the selected DAG. The scaled impulse responses to a shock in crude oil are larger in magnitude for corn, food CPI, and food PPI. The final response of food CPI does not appear to level out.

The remaining DAGs, 2, 4, 5, 6, and 7, possess the causal relationship of gasoline price to crude price. In the impulse response results given each of these DAGs, the response of food CPI to a shock to crude is the same as that for DAG 3; food CPI's scaled response is slightly larger in the later horizons than in the results given the selected DAG. As expected, the forecast error variance results for crude oil given each of these DAGs show that less variation in crude oil price is attributable to itself and more is attributable to gasoline and/or fuel PPI (dependent upon whether gasoline explains fuel PPI or vice versa), while gasoline accounts for more variation in its own price than in the results given the selected DAG with the exception of DAG 5.

The major conclusions based on the selected DAG: (1) that crude oil price, corn price, and the dollar index are the main contributors to food price variation; and (2) that ethanol price does not contribute to food or corn price variability, are also present given the other seven DAGs. Although the contemporaneous causal relationships differ between these DAGs, the inferences from the different DAGs concerning the main factors affecting food prices do not differ between the DAGs. Crude oil, corn price, and the dollar index remain the major contributors to food price variations. Additionally, ethanol price explains less than 1.5% of the uncertainty in each corn, food CPI, and food PPI.

CHAPTER V

CONCLUSIONS

The global food price surge in 2007-2008 and continued food price increases since have stimulated interest in the causal factors driving food prices. Adding to this interest is the ongoing debate regarding the role of grain-based ethanol in rising food prices. This recent concern over food prices has underscored the value of studies addressing food prices to policymakers, as well as, food processors, manufacturers, retailers, and consumers. The objective of this study, to identify how crude oil, gasoline, ethanol, and corn prices, the U.S. dollar exchange rate, and the producer price indexes for food manufacturing and fuel products affect domestic food prices, aims to add to the growing food price literature.

This study improves upon many earlier works in the literature by utilizing the U.S. Consumer Price Index for food (food CPI), rather than food grain commodity prices, to represent food prices. Food CPI allows for better inferences regarding the effects of system changes on the prices domestic food consumers pay at the supermarket.

The non-stationarity of the data series, as well as, cointegration among the series, dictated the use of a vector error correction model to capture the data generation process. A directed acyclic graph, obtained via the PC algorithm using the correlation matrix of the residuals from the estimated error correction model, represents the causal relationships among the series in contemporaneous time. This graph is used to conduct innovation accounting to observe the responses of each series to a one-time shock to each other series.

In terms of the “food versus fuel” debate, the results of the study suggest that ethanol price is not an important factor explaining domestic food prices. Forecast error variance results show that merely a fraction of the uncertainty in food CPI, food PPI, and corn prices can be attributed to information in ethanol prices. In fact, ethanol contributes little to any of the other series within the system. Moreover, impulse response results depict little reaction in these series to a one-time shock in ethanol prices. Series which do influence food CPI are crude oil price, corn price, and the U.S. dollar index. Information in each of these series contributes to the forecast error variance of food CPI in the middle and longer horizons. Additionally, both food CPI and food PPI exhibit large, positive responses to shocks in crude oil and corn price, suggesting that higher crude and corn prices may drive up food prices. Food CPI and food PPI respond negatively to a shock in the U.S. dollar index, indicating that changes in the foreign exchange value of the dollar may have an impact on food prices. Increases in the dollar index signal a strengthening U.S. dollar, which decreases the attractiveness of U.S. food exports, reducing foreign demand and domestic food prices, assuming no other changes. Additionally, demand for food imports into the U.S. may increase with more favorable trading terms, further contributing to reduced domestic food prices.

In consideration of the entire system, crude oil price and gasoline price are the major contributors of information accounting for uncertainty in the other series. Ethanol and food CPI, however, contribute little to the variation in series other than their own. The rejection of long-run exogeneity for all series indicates that the series work together to bring the system back into equilibrium. No series, consequently, is unaffected by the paths of other series in the system. Finally, results are robust in regards to the alternative DAGs.

Opportunities for Further Study

Limitations of this study, as well as, changes in the ethanol market, offer opportunities for additional research concerning the causal factors of food prices. First, better proxies for food manufacturing input costs and fuel production input costs may exist. The proxies used in this study, food PPI and fuel PPI, represent the prices producers receive for food and fuel products. Ideally, one would be able to represent the costs of food and fuel production directly so as to be able to estimate the effect of "other" input costs on the prices of the end products, gasoline and food CPI. The data for input costs other than those already included individually, however, was not available, forcing the use of the proxies. Second, the addition of other agricultural commodity prices to the system along with corn, such as wheat and soybeans prices, may provide a more complete picture of the factors affecting food prices. Because one of the goals of this study is to describe the relationship between food prices and ethanol prices, corn is the only agricultural commodity included. Third, further examination of the data suggests that using logarithms of the data series may not be appropriate. Comparison of the results using natural logarithms and the original series (not logged) should be undertaken. Finally, searching for structural changes may be appropriate, especially given the changing nature of the ethanol market. The institution of the RFS mandate, in particular, warrants further study for structural changes as ethanol production rose to meet the mandated levels.

Evolutions in the ethanol market may also warrant future study. For example, the fuel blender's federal tax credit for every gallon of ethanol blended into gasoline expired on December 31, 2011, two months before the time period of this study ends. Although the expiration of this tax credit will likely change the profitability of blending ethanol into gasoline, the effects of expiration given that the RFS mandate is still in place are unknown. Furthermore, the EPA approved the use of E15, which increases the allowable maximum of ethanol by volume in gasoline to 15% from 10% in late 2010. The use of E15, however, is only approved for vehicles of 2001 model year or later. Due in part to this restriction, the market has been slow to adjust to this new blend wall (EIA 2011b). Future increases in the volumes of ethanol blended into gasoline, however, could result in ethanol market adjustments. Finally, the possible shift from corn-based ethanol to cellulosic biofuel could also result in future market changes with spillover effects in the food, corn, and gasoline markets.

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APPENDIX A

Alternative directed acyclic graphs (figures A.1 – A.7) represent potential contemporaneous causal relationships among crude oil, gasoline, corn, and ethanol prices, as well as, the consumer price index for food (food CPI), producer price indexes for food and fuel (food PPI and fuel PPI), and the dollar index.

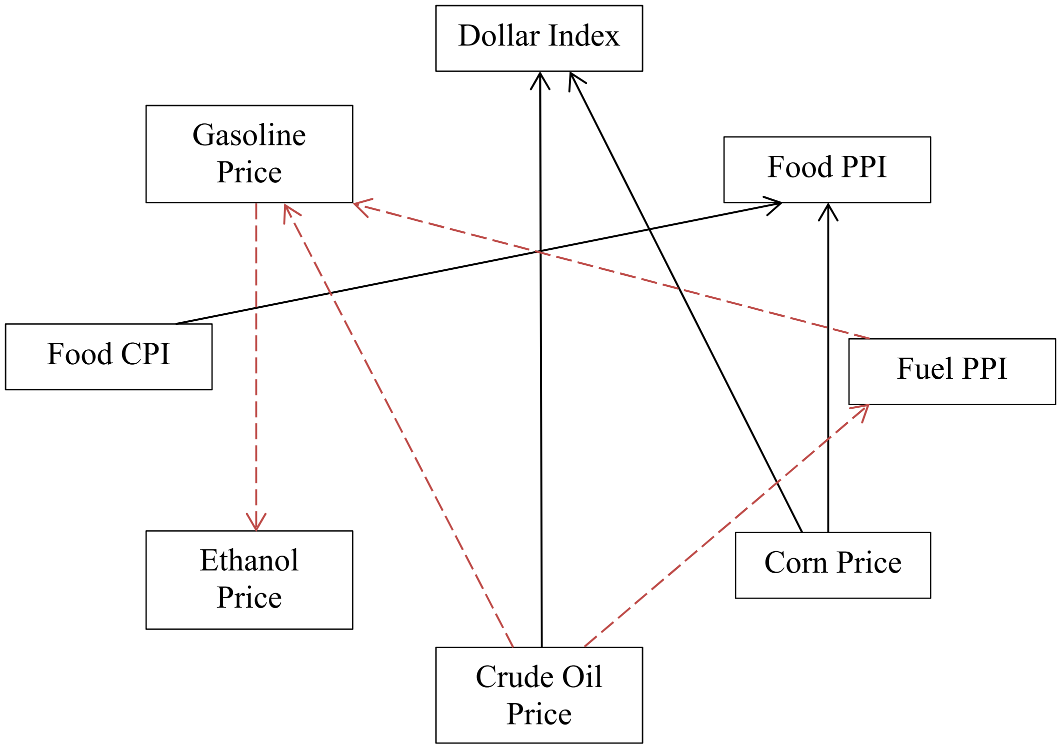

Figure A.1. Directed Acyclic Graph (DAG) 1

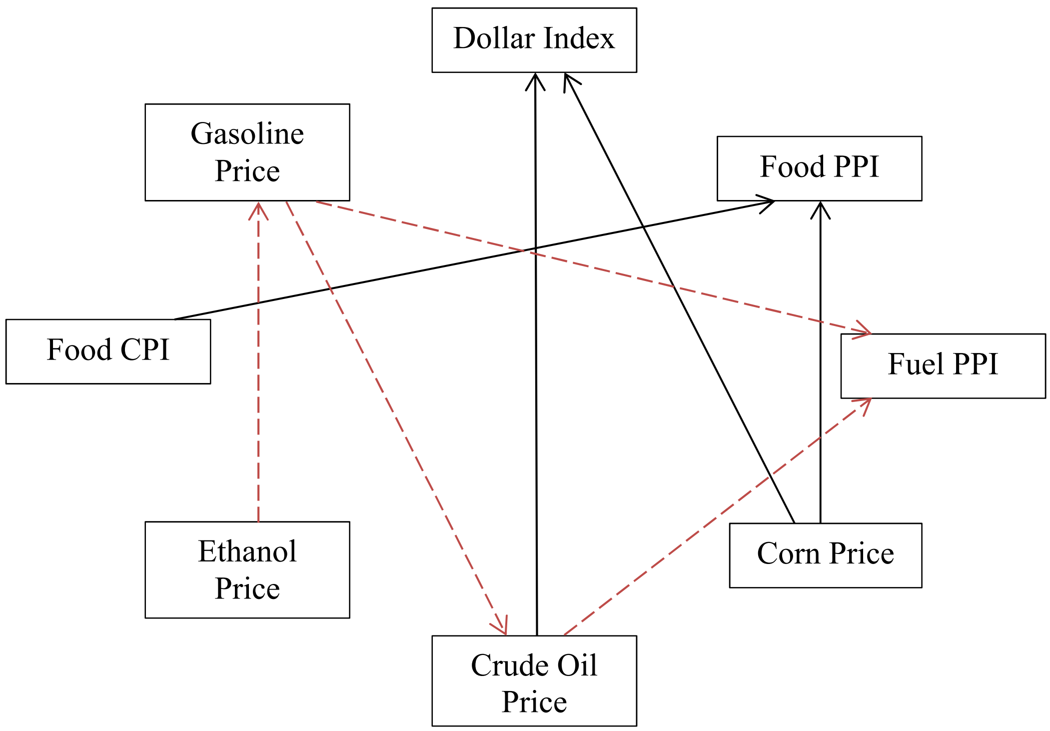

Figure A.2. Directed Acyclic Graph (DAG) 2

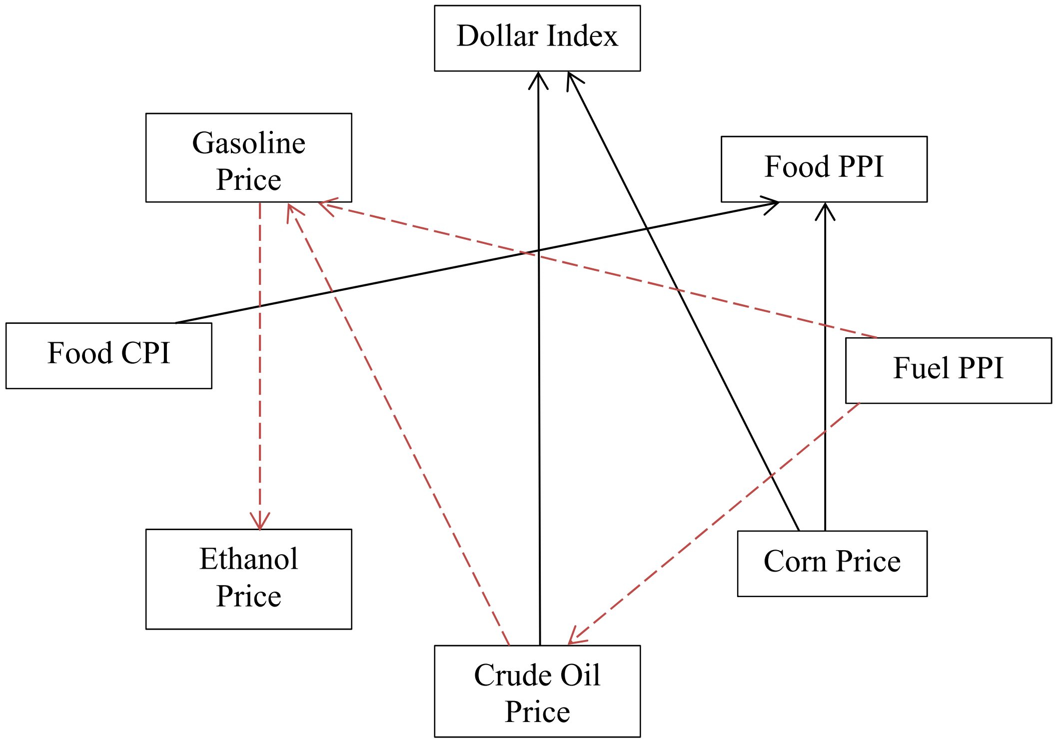

Figure A.3. Directed Acyclic Graph (DAG) 3

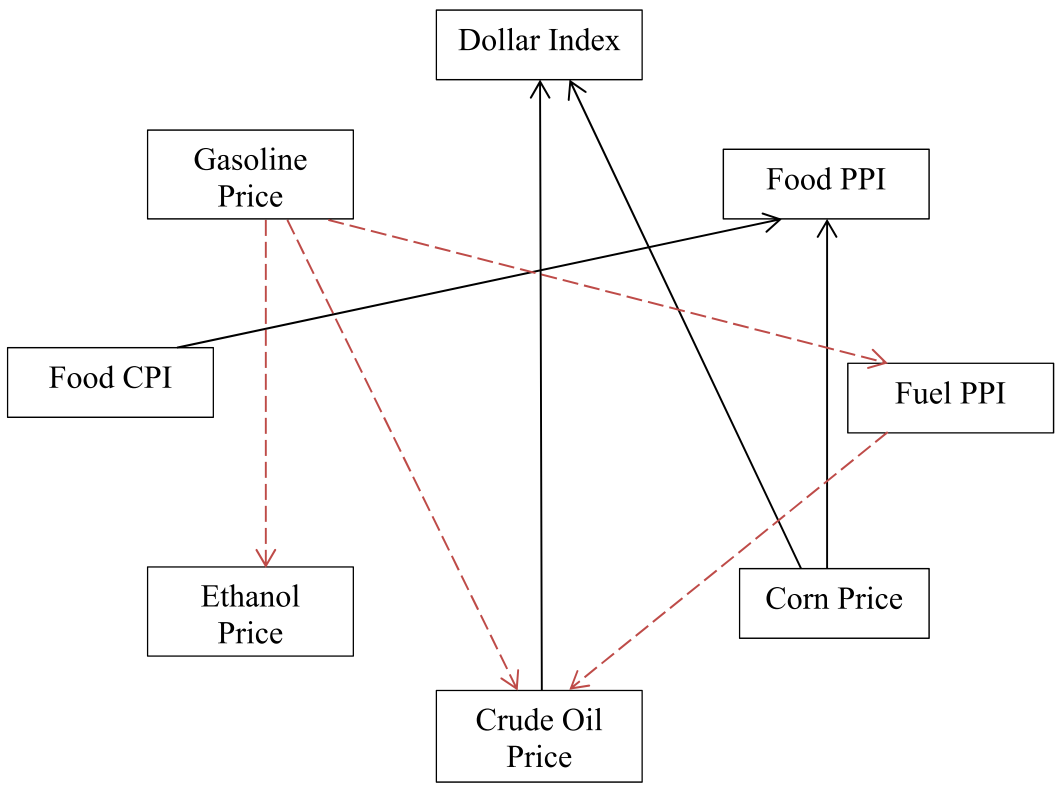

Figure A.4. Directed Acyclic Graph (DAG) 4

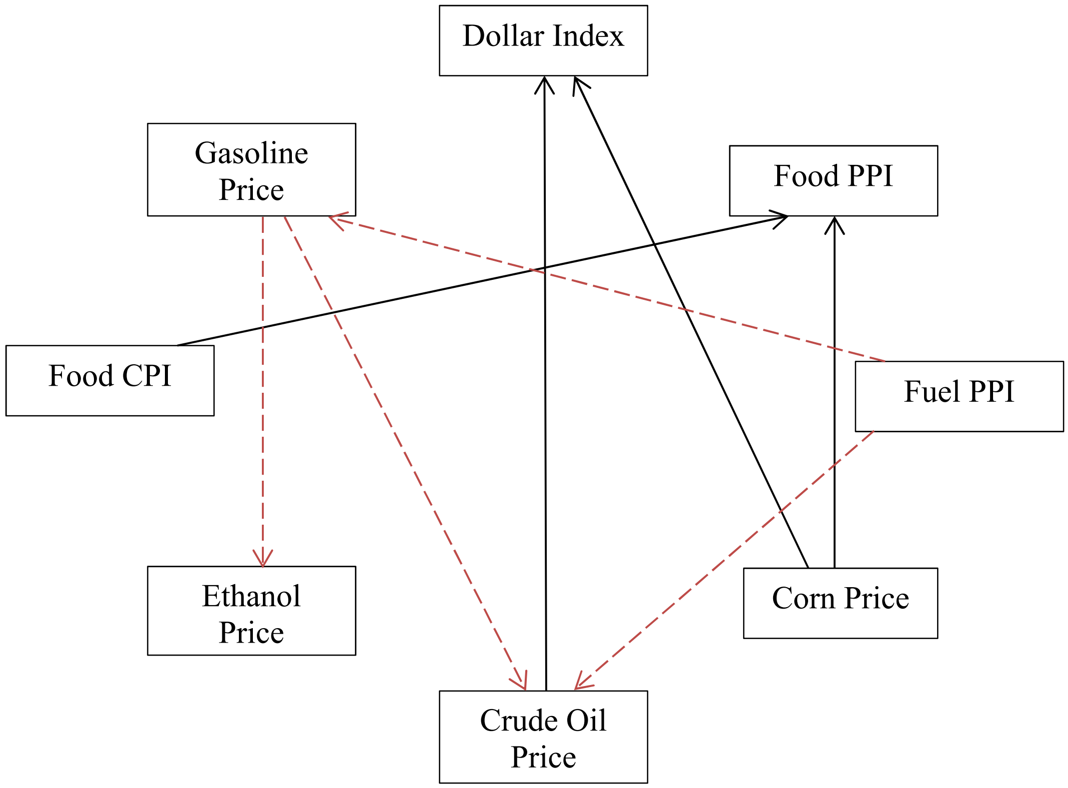

Figure A.5. Directed Acyclic Graph (DAG) 5

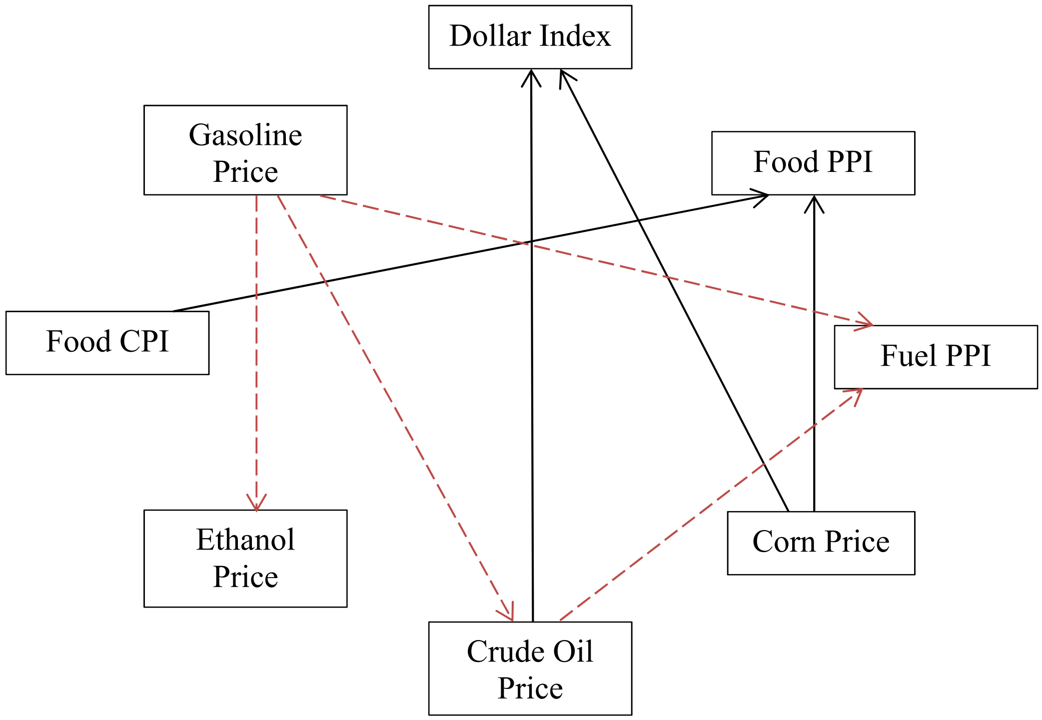

Figure A.6. Directed Acyclic Graph (DAG) 6

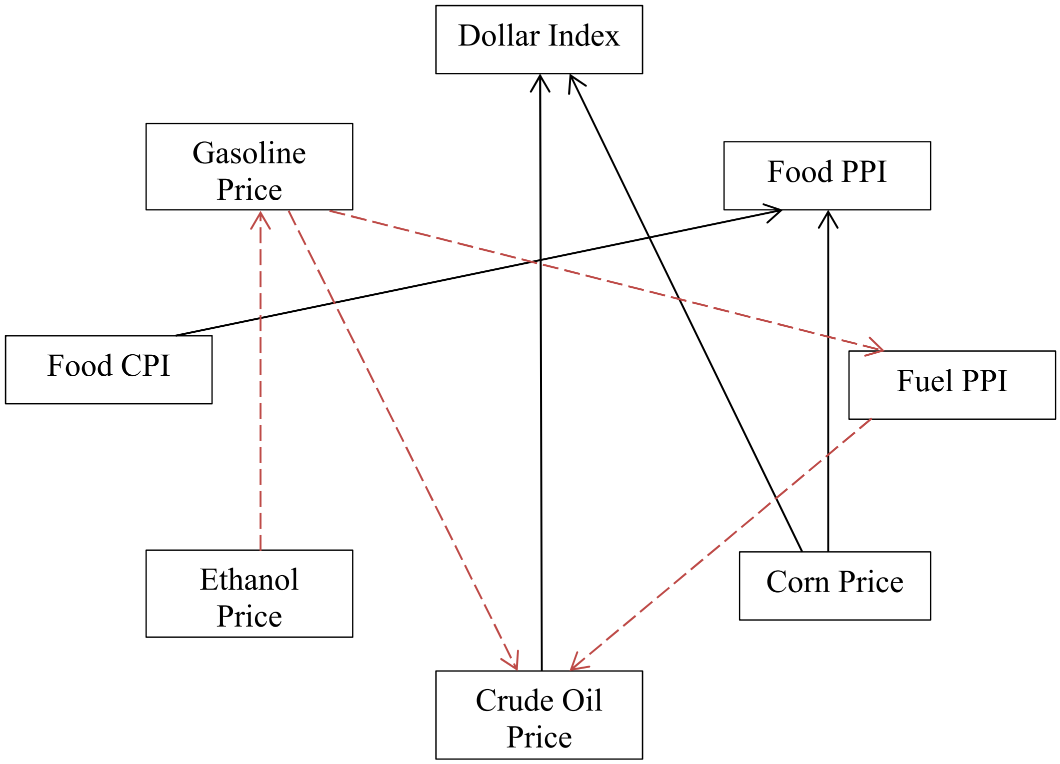

Figure A.7. Directed Acyclic Graph (DAG) 7

APPENDIX B

Impulse response function graphs (figures B.1 – B.7), corresponding to alternative DAGs 1-7 (figures A.1 – A.7), depicting the responses of each series (row headings) to a one-time shock to each of the other series (column headings) are shown.

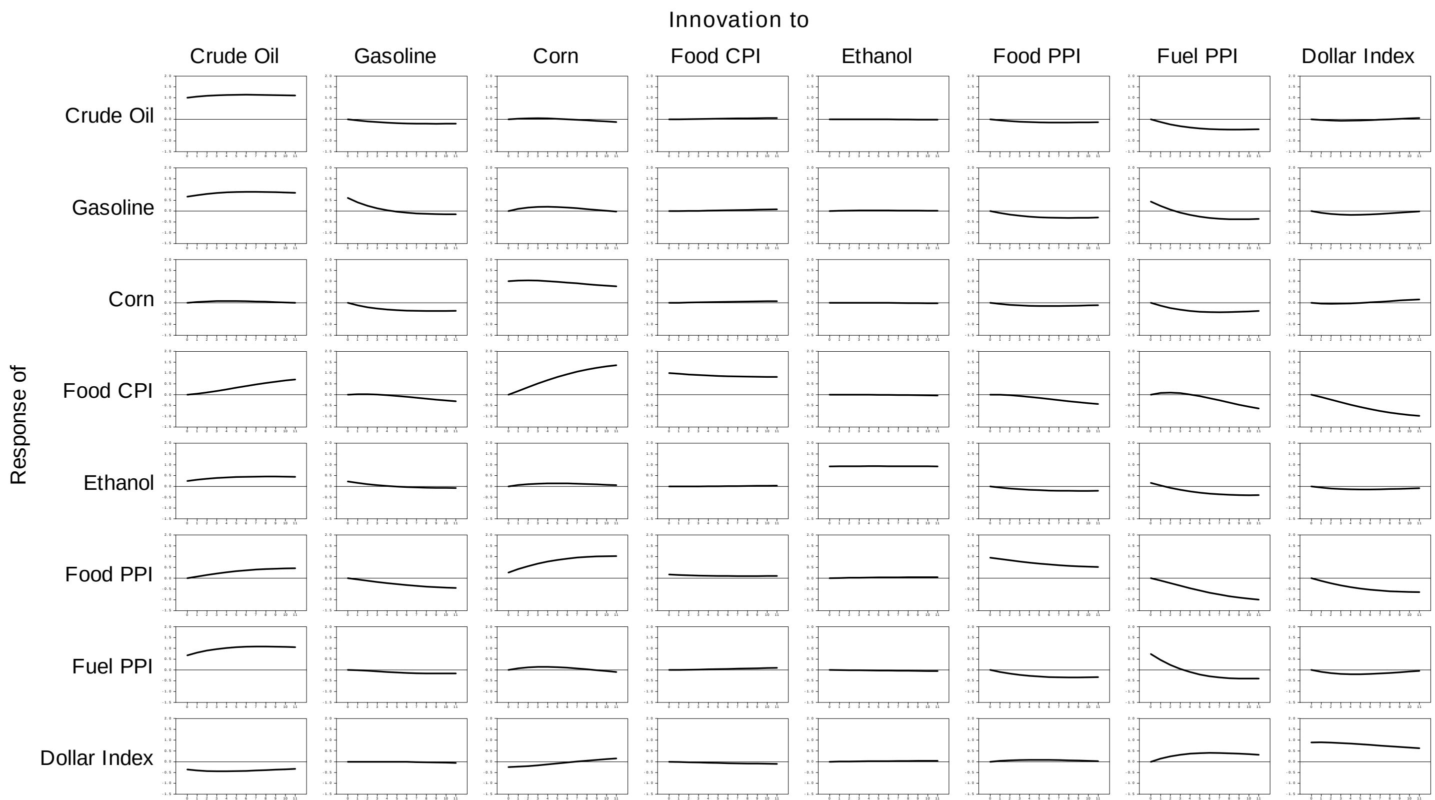

Figure B.1. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series Given DAG 1

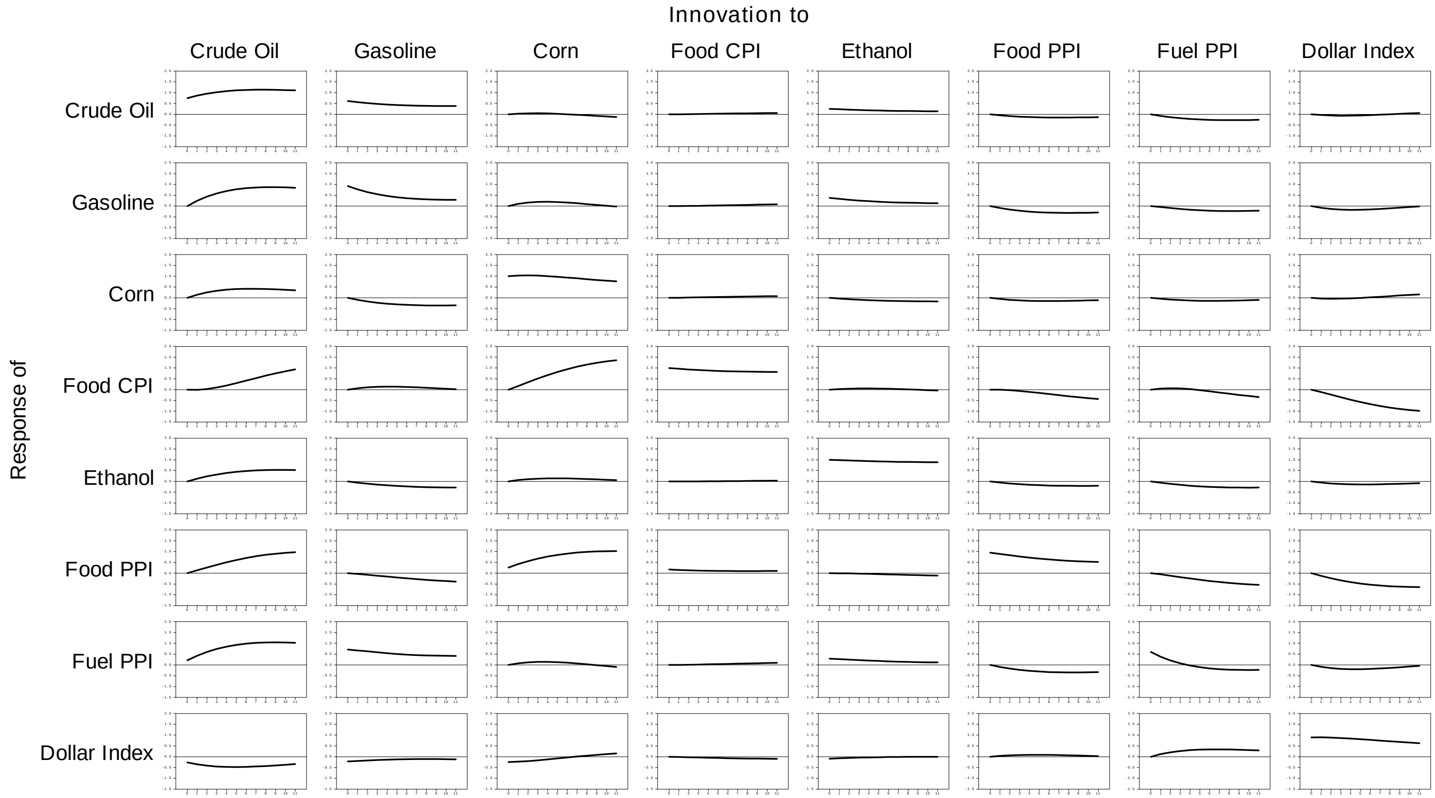

Figure B.2. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series Given DAG 2

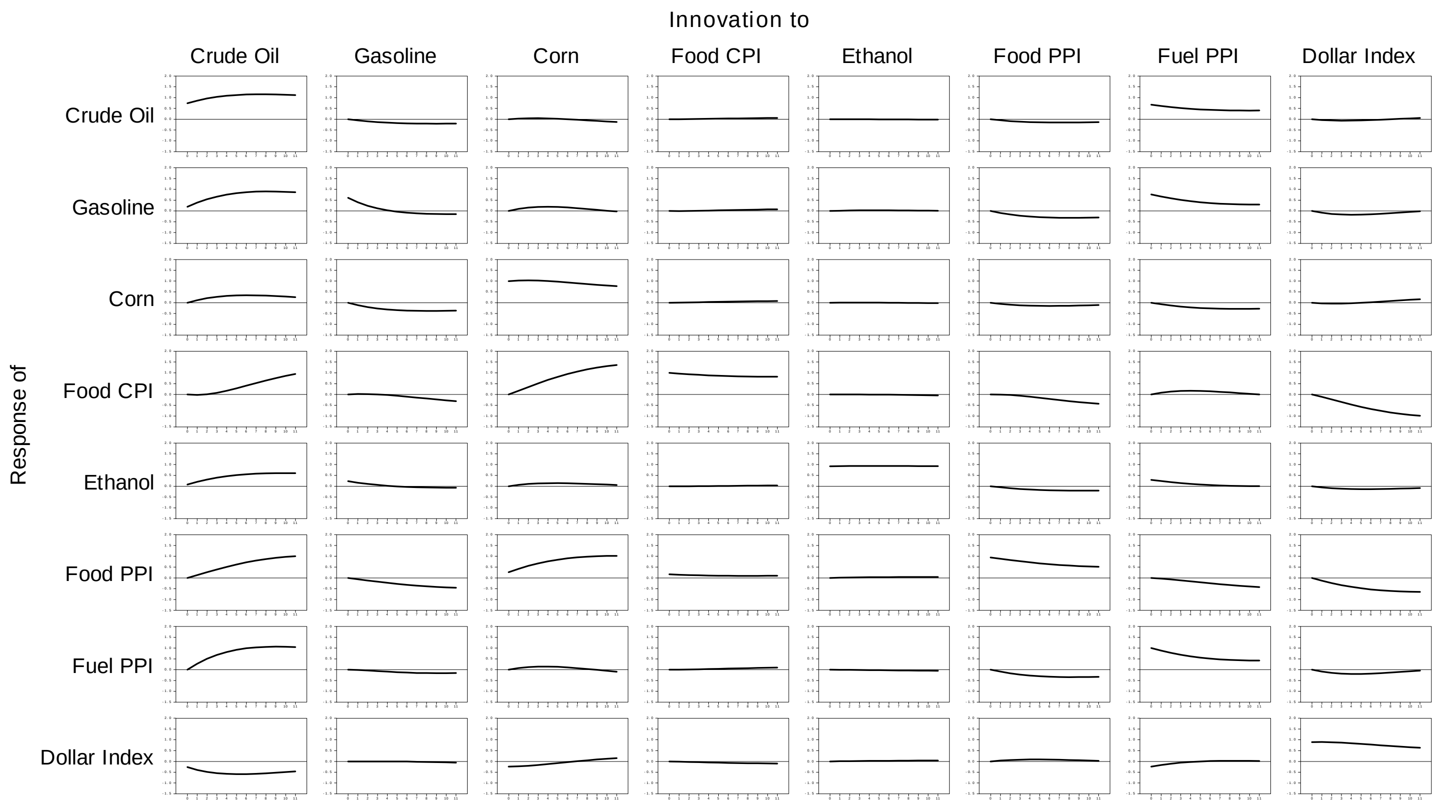

Figure B.3. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series Given DAG 3

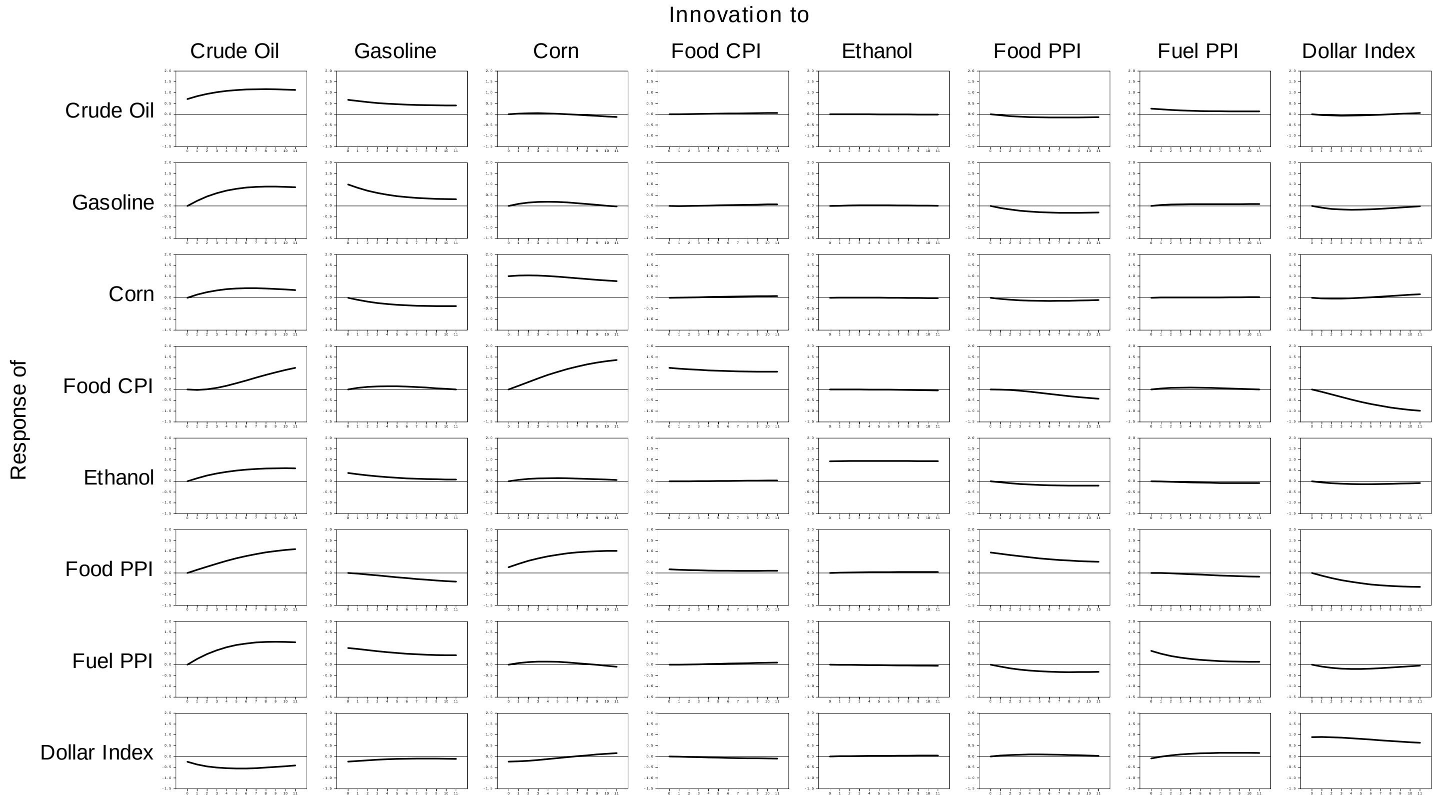

Figure B.4. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series Given DAG 4

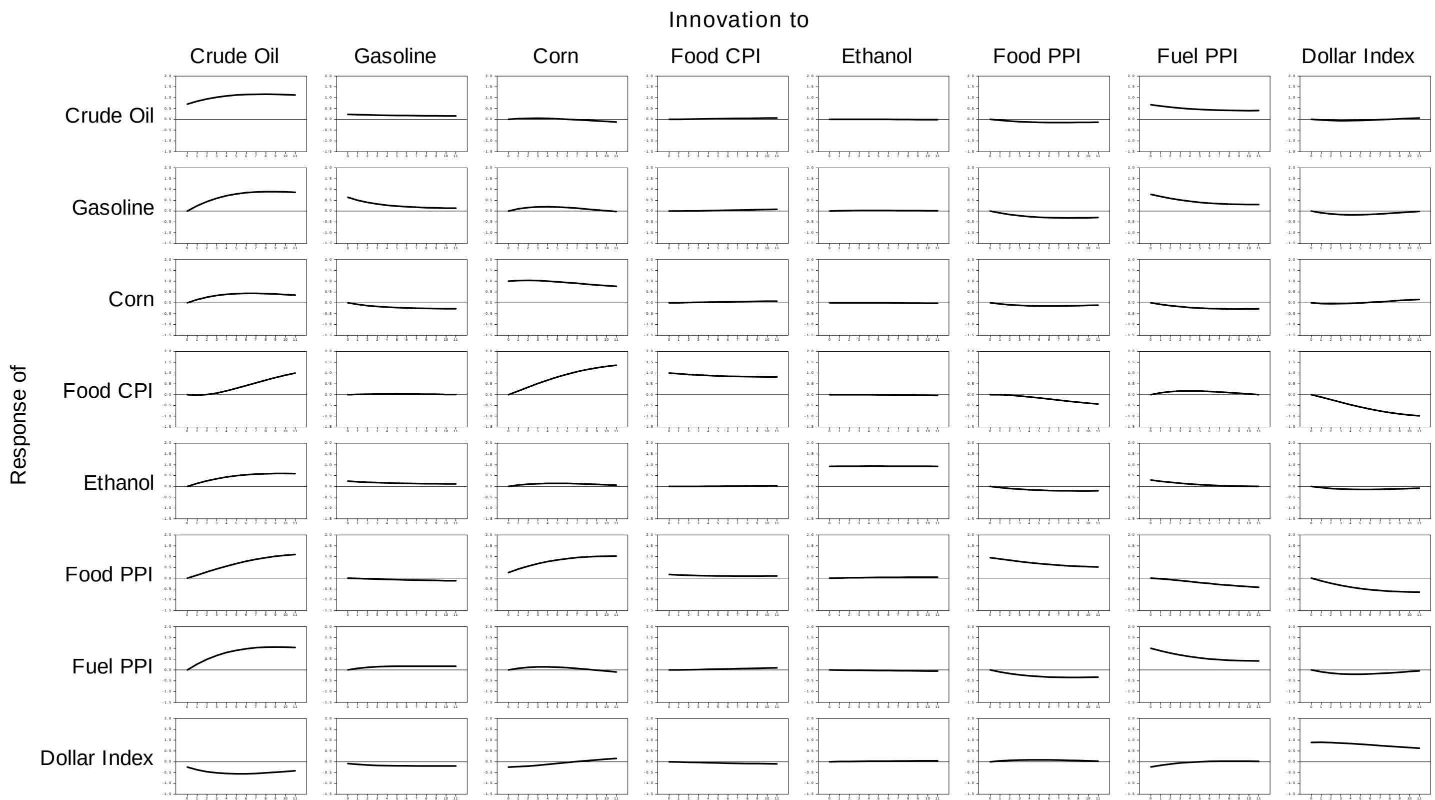

Figure B.5. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series Given DAG 5

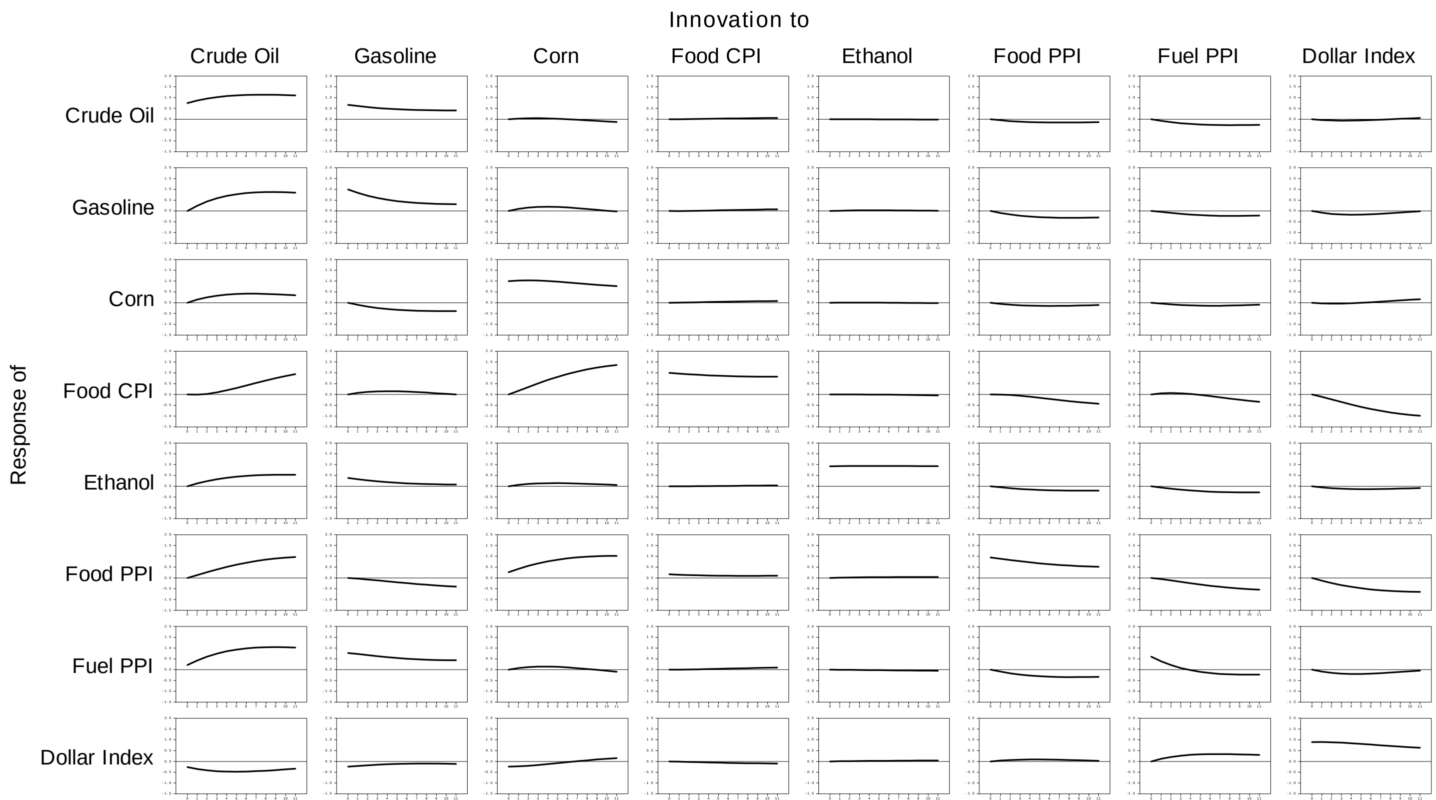

Figure B.6. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series Given DAG 6

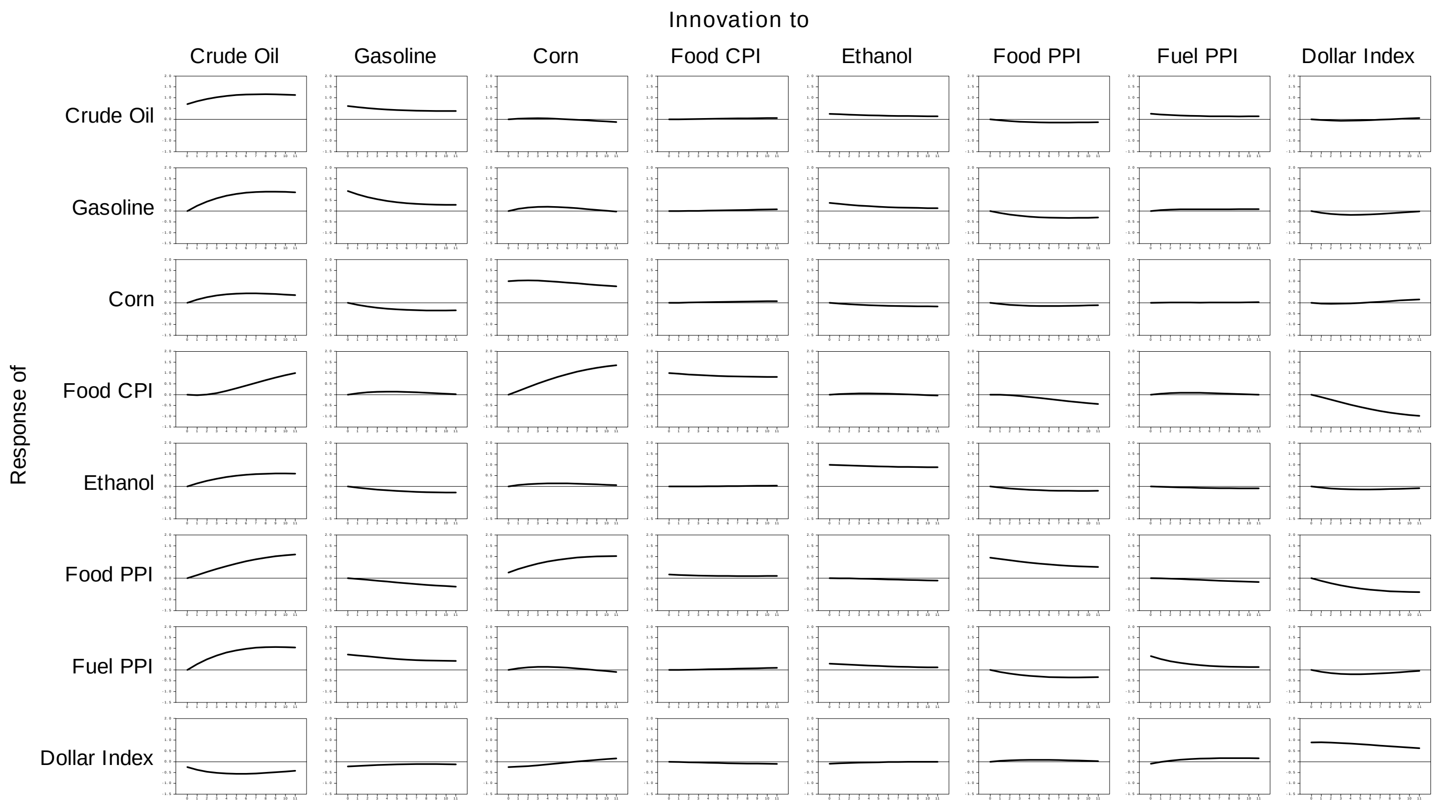

Figure B.7. Impulse Response Functions Depicting Responses of Each Series to a Shock to Each Other Series Given DAG 7

APPENDIX C

Forecast Error Variance Decompositions (figures C.1 – C.7) correspond to alternative DAGs 1-7 (figures A.1 – A.7). The percentage of variation in each series (subsections of each table) attributed to information in other series (column headings) at horizons 0, 1, 5, and 11 are given in the tables.

Table C.1. Decomposition of Forecast Error Variance for Each of Eight Series Given DAG 1

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	98.87	0.13	0.05	0.00	0.00	0.10	0.79	0.06
5	91.43	1.11	0.10	0.02	0.00	0.76	6.39	0.19
11	85.91	1.92	0.25	0.09	0.01	1.09	10.61	0.13
				Gasoline				
0	44.22	36.95	0.00	0.00	0.00	0.00	18.83	0.00
1	55.25	29.68	0.57	0.00	0.01	0.46	13.65	0.38
5	72.59	11.45	2.77	0.02	0.06	4.36	6.65	2.10
11	73.44	6.13	1.77	0.21	0.06	7.00	9.92	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.08	0.63	98.27	0.00	0.00	0.14	0.84	0.04
5	0.39	4.74	87.03	0.05	0.00	0.92	6.80	0.06
11	0.31	8.59	77.86	0.22	0.01	1.26	11.22	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.08	0.02	1.47	97.53	0.00	0.00	0.29	0.63
5	2.62	0.07	19.89	67.06	0.00	0.52	0.31	9.55
11	7.49	1.02	34.81	32.30	0.02	2.46	4.15	17.75
				Ethanol				
0	6.42	5.36	0.00	0.00	85.48	0.00	2.73	0.00
1	8.00	4.00	0.19	0.00	86.07	0.13	1.45	0.15
5	12.25	1.45	1.10	0.00	79.94	1.27	3.00	0.98
11	14.17	0.82	0.96	0.03	73.16	2.28	7.57	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	0.29	0.18	12.13	2.58	0.01	83.45	0.59	0.78
5	3.11	2.17	28.58	1.33	0.04	48.64	8.94	7.18
11	5.42	4.59	33.08	0.69	0.06	23.98	20.90	11.29
				Fuel PPI				
0	45.56	0.00	0.00	0.00	0.00	0.00	54.44	0.00
1	58.43	0.01	0.30	0.00	0.00	0.45	40.41	0.40
5	78.44	0.43	1.23	0.04	0.02	4.01	13.65	2.17
11	78.83	1.13	0.71	0.25	0.07	6.23	11.22	1.56
				Dollar Index				
0	13.01	0.00	6.07	0.00	0.00	0.00	0.00	80.92
1	14.33	0.00	5.54	0.01	0.00	0.07	1.01	79.03
5	16.80	0.00	3.21	0.12	0.03	0.44	7.72	71.68
11	17.28	0.07	2.27	0.45	0.09	0.45	12.09	67.31

Table C.2. Decomposition of Forecast Error Variance for Each of Eight Series Given DAG 2

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	55.78	37.80	0.00	0.00	6.42	0.00	0.00	0.00
1	61.23	32.72	0.05	0.00	5.58	0.10	0.26	0.06
5	72.84	20.52	0.10	0.02	3.47	0.76	2.09	0.19
11	77.85	14.80	0.25	0.09	2.38	1.09	3.41	0.13
				Gasoline				
0	0.00	85.48	0.00	0.00	14.52	0.00	0.00	0.00
1	3.31	80.90	0.57	0.00	14.29	0.46	0.09	0.38
5	31.64	48.03	2.77	0.02	9.36	4.36	1.72	2.10
11	53.21	27.40	1.77	0.21	5.57	7.00	3.37	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.98	0.43	98.27	0.00	0.06	0.14	0.08	0.04
5	7.02	3.61	87.03	0.05	0.56	0.92	0.74	0.06
11	10.56	7.17	77.86	0.22	1.35	1.26	1.06	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.00	0.21	1.47	97.53	0.04	0.00	0.13	0.63
5	1.79	0.93	19.89	67.06	0.14	0.52	0.14	9.55
11	11.07	0.39	34.81	32.30	0.06	2.46	1.17	17.75
				Ethanol				
0	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00
1	0.82	0.16	0.19	0.00	98.37	0.13	0.19	0.15
5	7.97	1.74	1.10	0.00	84.85	1.27	2.09	0.98
11	14.88	3.74	0.96	0.03	72.89	2.28	4.22	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	0.86	0.06	12.13	2.58	0.00	83.45	0.14	0.78
5	10.69	1.04	28.58	1.33	0.04	48.64	2.49	7.18
11	21.73	2.90	33.08	0.69	0.20	23.98	6.14	11.29
				Fuel PPI				
0	4.80	50.55	0.00	0.00	8.58	0.00	36.07	0.00
1	12.21	51.09	0.30	0.00	8.50	0.45	27.05	0.40
5	42.80	35.35	1.23	0.04	5.45	4.01	8.94	2.17
11	60.00	22.63	0.71	0.25	3.07	6.23	5.57	1.56
				Dollar Index				
0	7.26	4.92	6.07	0.00	0.84	0.00	0.00	80.92
1	9.71	4.27	5.54	0.01	0.67	0.07	0.70	79.03
5	16.32	2.71	3.21	0.12	0.32	0.44	5.20	71.68
11	18.49	2.22	2.27	0.45	0.19	0.45	8.64	67.31

Table C.3. Decomposition of Forecast Error Variance for Each of Eight Series Given DAG 3

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	54.44	0.00	0.00	0.00	0.00	0.00	45.56	0.00
1	60.53	0.13	0.05	0.00	0.00	0.10	39.12	0.06
5	73.91	1.11	0.10	0.02	0.00	0.76	23.91	0.19
11	79.65	1.92	0.25	0.09	0.01	1.09	16.86	0.13
				Gasoline				
0	3.91	36.95	0.00	0.00	0.00	0.00	59.14	0.00
1	10.50	29.68	0.57	0.00	0.01	0.46	58.40	0.38
5	41.16	11.45	2.77	0.02	0.06	4.36	38.08	2.10
11	60.27	6.13	1.77	0.21	0.06	7.00	23.09	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.68	0.63	98.27	0.00	0.00	0.14	0.24	0.04
5	4.92	4.74	87.03	0.05	0.00	0.92	2.27	0.06
11	6.93	8.59	77.86	0.22	0.01	1.26	4.61	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.02	0.02	1.47	97.53	0.00	0.00	0.34	0.63
5	1.54	0.07	19.89	67.06	0.00	0.52	1.40	9.55
11	11.10	1.02	34.81	32.30	0.02	2.46	0.55	17.75
				Ethanol				
0	0.57	5.36	0.00	0.00	85.48	0.00	8.58	0.00
1	2.30	4.00	0.19	0.00	86.07	0.13	7.16	0.15
5	11.89	1.45	1.10	0.00	79.94	1.27	3.36	0.98
11	20.18	0.82	0.96	0.03	73.16	2.28	1.57	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	0.84	0.18	12.13	2.58	0.01	83.45	0.04	0.78
5	11.01	2.17	28.58	1.33	0.04	48.64	1.04	7.18
11	23.04	4.59	33.08	0.69	0.06	23.98	3.28	11.29
				Fuel PPI				
0	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
1	4.13	0.01	0.30	0.00	0.00	0.45	94.70	0.40
5	36.34	0.43	1.23	0.04	0.02	4.01	55.75	2.17
11	58.39	1.13	0.71	0.25	0.07	6.23	31.66	1.56
				Dollar Index				
0	7.08	0.00	6.07	0.00	0.00	0.00	5.93	80.92
1	11.11	0.00	5.54	0.01	0.00	0.07	4.24	79.03
5	22.91	0.00	3.21	0.12	0.03	0.44	1.61	71.68
11	28.43	0.07	2.27	0.45	0.09	0.45	0.94	67.31

Table C.4. Decomposition of Forecast Error Variance for Each of Eight Series Given DAG 4

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	49.23	44.22	0.00	0.00	0.00	0.00	6.55	0.00
1	56.01	38.30	0.05	0.00	0.00	0.10	5.48	0.06
5	71.84	24.00	0.10	0.02	0.00	0.76	3.09	0.19
11	79.18	17.17	0.25	0.09	0.01	1.09	2.08	0.13
				Gasoline				
0	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
1	3.29	95.19	0.57	0.00	0.01	0.46	0.11	0.38
5	32.86	57.33	2.77	0.02	0.06	4.36	0.50	2.10
11	55.96	32.91	1.77	0.21	0.06	7.00	0.62	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	1.06	0.49	98.27	0.00	0.00	0.14	0.01	0.04
5	7.75	4.17	87.03	0.05	0.00	0.92	0.01	0.06
11	11.59	8.51	77.86	0.22	0.01	1.26	0.03	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.04	0.25	1.47	97.53	0.00	0.00	0.10	0.63
5	1.56	1.07	19.89	67.06	0.00	0.52	0.37	9.55
11	12.09	0.43	34.81	32.30	0.02	2.46	0.14	17.75
				Ethanol				
0	0.00	14.52	0.00	0.00	85.49	0.00	0.00	0.00
1	0.99	12.46	0.19	0.00	86.07	0.13	0.01	0.15
5	9.91	6.65	1.10	0.00	79.94	1.27	0.15	0.98
11	18.73	3.47	0.96	0.03	73.16	2.28	0.37	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	1.00	0.06	12.13	2.58	0.01	83.45	0.00	0.78
5	13.04	1.04	28.58	1.33	0.04	48.64	0.14	7.18
11	27.32	3.04	33.08	0.69	0.06	23.98	0.54	11.29
				Fuel PPI				
0	0.00	59.14	0.00	0.00	0.00	0.00	40.87	0.00
1	3.84	59.59	0.30	0.00	0.00	0.45	35.41	0.40
5	35.19	40.78	1.23	0.04	0.02	4.01	16.56	2.17
11	57.62	25.62	0.71	0.25	0.07	6.23	7.94	1.56
				Dollar Index				
0	6.40	5.75	6.07	0.00	0.00	0.00	0.85	80.92
1	9.99	4.94	5.54	0.01	0.00	0.07	0.42	79.03
5	20.63	3.00	3.21	0.12	0.03	0.44	0.89	71.68
11	25.18	2.31	2.27	0.45	0.09	0.45	1.95	67.31

Table C.5. Decomposition of Forecast Error Variance for Each of Eight Series Given DAG 5

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	49.23	5.21	0.00	0.00	0.00	0.00	45.56	0.00
1	56.01	4.65	0.05	0.00	0.00	0.10	39.12	0.06
5	71.84	3.18	0.10	0.02	0.00	0.76	23.91	0.19
11	79.18	2.39	0.25	0.09	0.01	1.09	16.86	0.13
				Gasoline				
0	0.00	40.86	0.00	0.00	0.00	0.00	59.14	0.00
1	3.29	36.90	0.57	0.00	0.01	0.46	58.40	0.38
5	32.86	19.75	2.77	0.02	0.06	4.36	38.08	2.10
11	55.96	10.44	1.77	0.21	0.06	7.00	23.09	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	1.06	0.25	98.27	0.00	0.00	0.14	0.24	0.04
5	7.75	1.92	87.03	0.05	0.00	0.92	2.27	0.06
11	11.59	3.93	77.86	0.22	0.01	1.26	4.61	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.04	0.01	1.47	97.53	0.00	0.00	0.34	0.63
5	1.56	0.04	19.89	67.06	0.00	0.52	1.40	9.55
11	12.09	0.02	34.81	32.30	0.02	2.46	0.55	17.75
				Ethanol				
0	0.00	5.93	0.00	0.00	85.49	0.00	8.58	0.00
1	0.99	5.31	0.19	0.00	86.07	0.13	7.16	0.15
5	9.91	3.44	1.10	0.00	79.94	1.27	3.36	0.98
11	18.73	2.27	0.96	0.03	73.16	2.28	1.57	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	1.00	0.02	12.13	2.58	0.01	83.45	0.04	0.78
5	13.04	0.14	28.58	1.33	0.04	48.64	1.04	7.18
11	27.32	0.30	33.08	0.69	0.06	23.98	3.28	11.29
				Fuel PPI				
0	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00
1	3.84	0.30	0.30	0.00	0.00	0.45	94.70	0.40
5	35.19	1.58	1.23	0.04	0.02	4.01	55.75	2.17
11	57.63	1.89	0.71	0.25	0.07	6.23	31.66	1.56
				Dollar Index				
0	6.41	0.68	6.07	0.00	0.00	0.00	5.93	80.92
1	9.99	1.12	5.54	0.01	0.00	0.07	4.24	79.03
5	20.63	2.28	3.21	0.12	0.03	0.44	1.61	71.68
11	25.18	3.32	2.27	0.45	0.09	0.45	0.94	67.31

Table C.6. Decomposition of Forecast Error Variance for Each of Eight Series Given DAG 6

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	55.78	44.22	0.00	0.00	0.00	0.00	0.00	0.00
1	61.23	38.30	0.05	0.00	0.00	0.10	0.26	0.06
5	72.84	24.00	0.10	0.02	0.00	0.76	2.09	0.19
11	77.85	17.17	0.25	0.09	0.01	1.09	3.41	0.13
				Gasoline				
0	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
1	3.31	95.19	0.57	0.00	0.01	0.46	0.09	0.38
5	31.64	57.33	2.77	0.02	0.06	4.36	1.72	2.10
11	53.20	32.91	1.77	0.21	0.06	7.00	3.37	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	0.98	0.49	98.27	0.00	0.00	0.14	0.08	0.04
5	7.02	4.18	87.03	0.05	0.00	0.92	0.74	0.06
11	10.56	8.51	77.86	0.22	0.01	1.26	1.06	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.00	0.25	1.47	97.53	0.00	0.00	0.13	0.63
5	1.79	1.07	19.89	67.06	0.00	0.52	0.14	9.55
11	11.07	0.43	34.81	32.30	0.02	2.46	1.17	17.75
				Ethanol				
0	0.00	14.52	0.00	0.00	85.48	0.00	0.00	0.00
1	0.82	12.46	0.19	0.00	86.07	0.13	0.19	0.15
5	7.97	6.65	1.10	0.00	79.94	1.27	2.09	0.98
11	14.88	3.47	0.96	0.03	73.16	2.28	4.22	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	0.86	0.06	12.13	2.58	0.01	83.45	0.14	0.78
5	10.69	1.04	28.58	1.33	0.04	48.64	2.49	7.18
11	21.73	3.04	33.08	0.69	0.06	23.98	6.14	11.29
				Fuel PPI				
0	4.80	59.14	0.00	0.00	0.00	0.00	36.06	0.00
1	12.21	59.59	0.30	0.00	0.00	0.45	27.05	0.40
5	42.80	40.78	1.23	0.04	0.02	4.01	8.94	2.17
11	60.00	25.62	0.71	0.25	0.07	6.23	5.57	1.56
				Dollar Index				
0	7.26	5.75	6.07	0.00	0.00	0.00	0.00	80.92
1	9.71	4.94	5.54	0.01	0.00	0.07	0.70	79.03
5	16.32	3.00	3.21	0.12	0.03	0.44	5.20	71.68
11	18.49	2.31	2.27	0.45	0.09	0.45	8.64	67.31

Table C.7. Decomposition of Forecast Error Variance for Each of Eight Series Given DAG 7

Horizon	Crude Oil	Gasoline	Corn	Food CPI	Ethanol	Food PPI	Fuel PPI	Dollar Index
				Crude Oil				
0	49.23	37.80	0.00	0.00	6.42	0.00	6.55	0.00
1	56.01	32.72	0.05	0.00	5.58	0.10	5.48	0.06
5	71.84	20.53	0.10	0.02	3.47	0.76	3.09	0.19
11	79.18	14.80	0.25	0.09	2.38	1.09	2.08	0.13
				Gasoline				
0	0.00	85.48	0.00	0.00	14.52	0.00	0.00	0.00
1	3.29	80.90	0.57	0.00	14.29	0.46	0.11	0.38
5	32.86	48.03	2.77	0.02	9.36	4.36	0.50	2.10
11	55.96	27.40	1.77	0.21	5.57	7.00	0.62	1.49
				Corn				
0	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
1	1.06	0.43	98.27	0.00	0.06	0.14	0.01	0.04
5	7.75	3.61	87.03	0.05	0.56	0.92	0.01	0.06
11	11.59	7.17	77.86	0.22	1.35	1.26	0.03	0.53
				Food CPI				
0	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00
1	0.04	0.21	1.47	97.53	0.04	0.00	0.10	0.63
5	1.56	0.93	19.89	67.06	0.14	0.52	0.37	9.55
11	12.09	0.39	34.81	32.30	0.06	2.46	0.14	17.75
				Ethanol				
0	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00
1	0.99	0.16	0.19	0.00	98.37	0.13	0.01	0.15
5	9.90	1.74	1.10	0.00	84.85	1.27	0.15	0.98
11	18.73	3.74	0.96	0.03	72.89	2.28	0.37	1.01
				Food PPI				
0	0.00	0.00	6.88	2.96	0.00	90.16	0.00	0.00
1	1.00	0.06	12.13	2.58	0.00	83.45	0.00	0.78
5	13.04	1.04	28.58	1.33	0.04	48.64	0.14	7.18
11	27.32	2.90	33.08	0.69	0.20	23.98	0.54	11.29
				Fuel PPI				
0	0.00	50.55	0.00	0.00	8.58	0.00	40.86	0.00
1	3.84	51.09	0.30	0.00	8.50	0.45	35.41	0.40
5	35.19	35.35	1.23	0.04	5.45	4.01	16.56	2.17
11	57.62	22.63	0.71	0.25	3.07	6.23	7.94	1.56
				Dollar Index				
0	6.40	4.92	6.07	0.00	0.84	0.00	0.85	80.92
1	9.99	4.27	5.54	0.01	0.67	0.07	0.42	79.03
5	20.63	2.71	3.21	0.12	0.32	0.44	0.89	71.68
11	25.18	2.22	2.27	0.45	0.19	0.45	1.95	67.31